THE FLORIDA DEPARTMENT OF TRANSPORTATION

TRAFFIC ENGINEERING AND OPERATIONS OFFICE

Traffic-event Unification System Highlighting Arterial Roads

Technical Memorandum

TASK 1 (Research Existing, Develop New, and Prioritize Machine Learning Algorithms for Incident Detection in Traffic Control)
and
TASK 3 (Conduct Literature Survey for Fusion and Incident Detection with a focus on transportation applications)

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1. Introduction

This report presents the supporting tasks and deliverables for Task 2 of the project.

The deliverables defined for this task were as follows:

Task 1 – Research Existing, Develop New, and Prioritize Machine Learning Algorithms for Incident Detection in Traffic Control

Conduct a literature review of existing applications of the use of machine learning algorithms for incident detection in traffic control and document possible new approaches that may be relevant.

Task 1 Deliverable: Upon completion of Task 1, the University will submit to the Research Center at research.center@dot.state.fl.us a written Technical Memorandum detailing the literature review.

Task 3 – Conduct Literature Survey for Fusion and Incident Detection with a focus on transportation applications

We will conduct a detailed literature survey of the use of intersection control data and

- **Strengths and weaknesses of current approaches for fusion data.**
- **Strengths and weaknesses of current approaches for incident detection.**

Whenever reasonable and feasible, the work will incorporate best practices and business glossary for data as per the ROADS initiative.

<u>Task 3 Deliverable</u>: Upon completion of Task 3, the University will submit to the Research Center at research.center@dot.state.fl.us written a Technical Memorandum that provides a description of current approaches for fusion and incident detection with a focus on transportation applications.

The specific subtasks are outlined as follows along with the section numbers in the report that pertain to these subtasks.

1. Conduct a literature review of existing applications of the use of machine learning algorithms for incident detection in traffic control (Section 7)
2. Document possible new approaches that may be relevant (Section 7,10)
3. We will conduct a detailed literature survey of the use of intersection control data and PCD data (Section 3,4,5,6)
4. Strengths and weaknesses of current approaches for fusion data (Section 9)
5. Strengths and weaknesses of current approaches for incident detection (Section 7,10)

2. Background

Automated Incident Detection (AID) is of significant interest in modern transportation networks. This is because traffic incidents and congestion can impede commercial activities and hurt the economic growth of a region. By detecting incidents quickly, the incident-response times can be reduced, along with the negative impacts of the resultant congestion and secondary incidents.

While direct and manual TMC monitoring has been adequate for previous years, many TMCs have had limited operational use of automatic incident detection techniques. This is due to these techniques' high rates of false alarms, complex calibration and low detection rates [1]. In fact, many automatic incident detection algorithms perform poorly in the real-world compared to traffic simulated environments [2]. However, the steady growth and development in transportation networks has motivated a need for highly-reliable automated methods to detecting incidents on urban transportation networks.

Advanced Incident Detection algorithms using computational statistics or machine learning has been the research community's most recent offering on this subject. Significant efforts have been made to apply techniques such as genetic algorithms [4], Bayes classifiers [5], support vector machines [6] [7] [8], neural networks [9] [10] [11], deep learning [12] [13], fuzzy logic [13] [14], wavelet transformation [15][16] [17] and other artificial intelligence techniques [18] for incident detection. These modern techniques are data-centric, using historic and real-time data to detect various types of traffic incidents. Consequently, these advanced solutions are only as good as the data they are built on.

Arterial roads have different characteristics from freeways, since arteries feature more dynamic traffic due to the influence of several factors: (1) closely-spaced traffic signals and intersections, (2) dynamic queues at the intersections, (3) pedestrian crossings and jaywalking, (4) road-side parking, (5) exit/entry into/from collector-lanes, (6) public transport bus-stops, (7) arterial road-work, etc. These factors make incident detection on arteries potentially more difficult. While, solutions for arterial roads must consider data from heterogeneous sources in order to account for the complicating factors mentioned.

In this survey, existing machine learning algorithms for incident detection in traffic control are reviewed and evaluated. While data from FDOT detectors, probe cars, Twitter, and human reporting/event verification systems will each have a differential impact on the accuracy of incident detection, modern data fusion techniques could enhance the overall quality of combined traffic information. We summarize the successful techniques in this area along with the corresponding performance criteria, and document possible new approaches.

A traffic *incident* is a non-recurring and unexpected occurrence that has a noticeable undesirable effect which could temporarily disrupt traffic on some segment of the transportation network [1] [3]. An *incident detection*, on the other hand corresponds to generation of an incident report [3]. Examples of traffic incidents are traffic accidents, non-recurrent congestion, abandoned or stalled vehicles, spillage of oil or debris, structural fires, etc. Timely incident detection is important since it allows emergency responders to address the incident promptly, and enables traffic management centers to redistribute and reroute the oncoming traffic into alternate lanes in the transportation network. This reduces the impact of the primary incident, and avoids creating secondary incidents or follow-on congestion.

Incident detection solutions may be manual or automatic. While manual solutions are based on human reporting systems, automatic incident detection (AID) algorithms attempt to automatically setoff an alarm using anomaly detection techniques with respect to traffic conditions. The following list [1] [2] shows the developments in AID algorithms research with respect to statistics and pattern-recognition:

- Standard Normal Deviate algorithm [19]
- California family of algorithms [20][21]
- Bayesian algorithms [22][23]
- Time Series algorithms [24]
- Smoothing/Filtering algorithms [25][26]
- Traffic Modeling algorithms [27]
- McMaster catastrophe theory-based algorithm [28]
- Image Processing algorithms [29][30]
- MIT algorithms [31]
- ADVANCE algorithms [3][32]
- TTI algorithms [33]
- UCB algorithms [34]
- TRANSMIT algorithms [35][36]
- Waterloo algorithms [37]

In the last two decades, data-centric algorithms based on computational statistics and machine learning have been developed to produce advanced incident detection algorithms. These advanced algorithms are superior in terms of their performance, as measured by the standard performance metrics. Three performance criteria for incident detection are as follows:

1. Detection Rate (DR): Fraction of actual incidents that are correctly categorized as incidents.
2. False Alarm Rate (FAR): Fraction of actual incidents that are correctly categorized as incidents. FAR corresponds to fraction of non-incident periods that the algorithm incorrectly categorizes as incidents [3].
3. Mean Time to Detect (MTTD): Average response time of the algorithm.

There is usually a trade-off, as well as a compromise, between these the above performance factors. While Ren, Jimmy SJ et al. (2012) [65] demonstrate trade-offs between FAR and MTTD, several TMCs acknowledge that early detection is more important than a high detection rate. Lastly, the algorithm's ease of calibration is another important factor taken into consideration by TMCs when adopting an AID solution.

3. Data Sources

The performance of the algorithms depends on the quality of the traffic data collected. Reliable sensor technologies and data feeds provide data with high accuracy, granularity and wide spatio-temporal coverage. There are three major sources of data used for automatic incident detection:

1. Traditional Signal Systems (Roadway based Fixed Point/Section)
2. Probe-based (Floating Car)
3. Human reporting systems/Event verification/Driver based

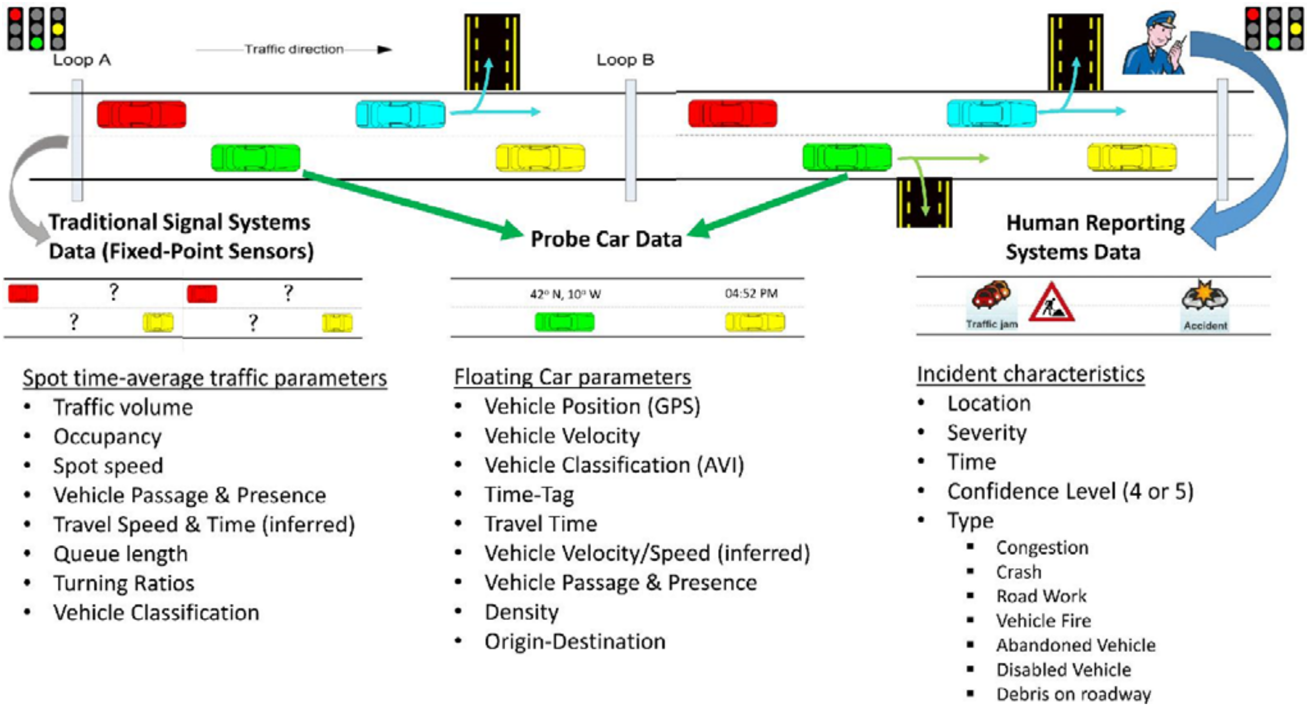

Figure 1: Traffic data sources and their respective data-of-interest

4. Traditional Signal Systems

Traditional Signal Systems sensors are fixed and measure traffic at a single point/section of a roadway. These systems exist in all urban areas, most of suburban areas, but are limited in rural areas. These include Inductive Loop Detectors (ILD), loop emulators, sensors (microwave, radar, infrared, ultrasonic, acoustic), pneumatic tubes, cameras and video image processors. Data collected includes traffic volume, occupancy, spot speed, vehicle passage/presence, queue length, turning ratios, vehicle classification, travel speed, travel time, etc.

AID algorithms using signal systems roadway data rely heavily on adjacent fixed detectors. Apart from an incident possibly reducing traffic flow at nearby detectors, the basic assumption is that an incident would cause a substantial increase in occupancy at the upstream detector, while producing a corresponding decrease in occupancy at the adjacent downstream detectors [38][39][40][41][42][43]. Existing works compare the space-time occupancy to a particular threshold value. However, selection of different threshold values produce very unique results. The California algorithm [38] estimates this threshold value using historical traffic data, and detects incidents by taking into account the absolute difference in occupancy of adjacent detectors as well as the relative difference with respect to the upstream or downstream detector. Fluctuations in occupancy can occur due to loop-detector errors and statistical variations. Hence, a range of values can be defined in order to identify the start (out-of-range) or the termination (back-in-range) of an incident [39]. Smoothed-averages and exponential-smoothing were old methods for estimating the threshold will mostly be effective for incidents that occurred close to a detector [40] [41]. Kalman filtering was another popular technique to estimate traffic flow, speed and occupancy [42] [43], but it would produce algorithms whose calibration was quite complex. There was a need for new approaches to accurately estimate the occupancy threshold value.

While conventional solutions, which apply fixed-threshold values for traffic occupancy, speed and volume, suffer from high false alarm rates, modern solutions [44] [45] [46] adapt their threshold-values based on real-time traffic data . The multiresolution property of wavelet transforms can be used to vary the threshold values for incident detection [44] [45]. Discrete wavelet transforms would be used to decay traffic data into different resolution–time elements in order to extract occupancy and speed data. This would produce threshold values that fluctuate in relation to the traffic measurements. The threshold can also be based on the level of demand on a roadway segment. Asare et al. [46] use the Hilbert-Huang transform to decompose traffic data, exploiting the empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA) to adaptively change the threshold to correspond to the current demand level. Both Wavelet transforms and Hilbert-Huang transforms produce algorithms with the highest Detection Rate, lowest False Alarm Rate and shortest Mean–Time-To-Detection, compared to existing fixed point solutions.

Fixed point detectors are restricted to providing traffic-data from limited fixed points in the roadway. Hence, it is difficult to use this data to realistically model the traffic conditions that are spatially continuous.

5. Probe Based Systems

Probe based sensors are usually mounted on individual vehicles that are mobile, and provides data at a single point, pair of points and sections. The reliability of probe data depends on the penetration rate, but it can measure a wider-area of a roadway compared to fixed sensors. Floating cars can provide traffic measurements in real-time with good spatial and temporal coverage at a very inexpensive cost. Probe data is provided by several third-parties like Here.com, TrafficCast, etc. These sensors include GPS receivers, Bluetooth readers, Toll Transponders, e-Tag readers, on-board units, smartphones, and any other in-vehicle telematics. Data collected includes origin-destination data, timestamp, location, speed, direction, density, queue length, turning ratios, route preferences, mode sharing, etc.

The main assumption behind using probe car data is that probe vehicles that pass an incident would have a relatively higher total time, coefficient of speed variation, and travel time[32][33][35]. The travel time during an incident is very high when compared to non-incident conditions from compare time of the day and day of the week [33] [35] [37] [58]. Furthermore, it has been shown that the travel time for a road section increases more quickly due to the capacity decrease caused by an incident as compared to increased demand [37]. Hence, it is believed that travel times before and after an incident should be viewed as belonging to two different populations. Probe car data comprised of traffic measurements for a link is very useful if the incident occurs downstream from that same link, but not upstream [3], and AID algorithms perform better when this probe car data measurement is more detailed [32].

A high penetration rate is crucial for Probe data based algorithms, which may perform worse than fixed detector based algorithms when the penetration rate is low [33] [35]. If the algorithm is based on mean travel-time, then a 50% penetration is required for good performance [59]. Petty et al. (1997) [34] provides a model that can be useful in estimating an upper-bound on the detection rate for probe vehicle density in a defined cell. They claim that only a single probe vehicle is required in a defined cell, in order to detect the incident occurrence within that cell.

Probe data covers longer sections of the urban roadway than fixed detectors, and is especially useful for detecting secondary incidents or non-recurrent congestion which are likely to occur away from the primary incident[48][53].

6. Human Reporting Systems

Human Reporting Systems provides anecdotal information from incident reports made directly by drivers, road crews, patrol units, and other travelers on the road. This type of incident detection is manual rather than automated, but it provides a very rich source of information because the incident can be described very clearly with regard to its location, time, type, and severity [54] [55]. Driver based reports over the cellular phone is usually the fastest mode of incident detection [1], and requires very less investment for operation and maintenance.

However, these reports are difficult to process and could contain false reports due to mistakes or malice. Mussa, R., & Upchurch, J. [56] [57] show that an incident detection system using cell phone calls (or tag-based digital messaging) from drivers could have lower Detection Times and higher Detection Rates. However, they do not completely consider malicious incident reports. Sources include Twitter tweets, wireless/cellular phone reports, roadside call boxes, patrol crew, road crew, Waze, etc.

Twitter is a very inexpensive method for incident detection. However, it is very brittle due to dependence on the Social-Media organization to allow access to the data. Gu et al. (2016) [66] presents methods to classify tweets. Tweets can be acquired in real-time using Twitter's streaming REST API and using a set of important keywords that could imply traffic incidents. They use this information to classify each tweet as an incident or non-incident, and then categorized them by location. They claim that there is more incident information on Twitter during the weekends and during the daytime, 60-70% are posted by influential users, and the tweets are usually about incidents that are closed to the center of a city. Studies have been performed to determine the value of tweets in incident detection [67] where they selected features in order to extract both the individual and paired token features from Twitter's social media site. They address several issues for detecting incidents from tweets: such as the language customs that Twitter users would frequently use to describe a traffic incident, the time, location and user influence bias.

7. Incident Detection Algorithms

Threshold Based Systems: Conventional incident detection algorithms use threshold-values to determine if an incident has occurred. A system that compares against precise threshold values cannot consistently classify incident vs non-incident conditions in an accurate manner. This is due to the lack of quality (loss/approximation of information) in the available traffic data, or even an overlapping membership in multiple sets, such as an incident spread spatio-temporally over multiple links [48]. As a result, this ambiguity may cause lower detection rates and higher false alarm rates. Fuzzy Logic can minimize error due to uncertainty in parameters by providing approximate reasoning instead of precise reasoning. It provides membership functions, with a range between 0 and 1, that represent the odds of membership in a particular set. After all calculations and computations are completed, if the cumulative membership value is greater than some threshold, the membership to that particular set holds true.

AID solutions using Fuzzy Logic are simpler to calibrate, maintain and debug when compared to other AID algorithms [49] [50] [51]. In machine learning solutions [52], Fuzzy Logic can be used to reduce errors, speed up convergence, and control the parameters or learning rate of the model in order to avoid overshooting during the training period. Chang, E. C. P., & Wang, S. H. (1994) [50] stress the necessity of automated learning techniques in incident detection. Hence, marrying machine learning with fuzzy logic would undoubtedly benefit AID algorithms by minimizing error due to uncertainty in data points.

Neural Networks: Artificial neural networks (ANNs) are computing systems that learn to make decisions in the absence of specific rules, by considering examples instead. With respect to incident detection, Cheu and Ritchie (1995) [10] found that multi-layer feed-forward neural networks performed better than self-organizing feature maps (SOFM) and adaptive resonance theory model 2 (ART2). Neural networks (NN) have been used to estimate traffic volumes [70] and incident detection [71]. However, constructive probabilistic neural networks (CPNN) can use a smaller sized network to achieve the same results [72]. Ivan and Sethi (1998) [71] focus on identifying the factors that would predict the occurrence of traffic incidents. They show that by adjusting the algorithm's inputs to avoid false alarms, neural networks can perform better than discriminant analysis models. Furthermore, their results indicated that additional inputs, like historical input-output data of the algorithm along with conditions of adjacent links, would further improve detection rates and false alarms. Hence, they trained and connected three more neural networks providing these data. They found significant performance improvement with the addition of each extra type of input data, with the full network demonstrating the best performance. Their results suggest that time series is beneficial to the solution. The performance of neural networks can also be improved by careful selection of parameters. For example, Roy and Abdulhai (2003) [4] use genetic algorithms to optimize the selection of parameters in a probabilistic neural network (PNN) and achieve lower detection rates while experiencing less false alarms. Similarly, fuzzy logic [13] has also been used for controlling the parameters in neural networks. Dia and Rose (1997) [9] use a multilayer perceptron neural network to detect incidents. The authors also evaluate the relevance of data quality with respect to the model's performance. For detecting traffic incidents, or even arterial operational problems, neural networks generally perform better than other types of classifiers [71] [47], except possibly support vector machines.

Support Vector Machine (SVM): is suitable for finding the global best solution when dealing with small sample data and non-linear but high-dimensional problems and has been found to be good machine learning technique used to detect traffic incidents [60]. SVM for incident detection has a higher detection rate, lower false alarm rate, and shorter average detection time than multi-layer feed forward neural networks [51]. Ant Colony Algorithm (ACA) has been used for parameter selection that is crucial for its learning accuracy and generalization ability [7] [61]. Shuyan Chen et al. [61] combines an ensemble of SVM classifiers for traffic incident detection, and in doing so, they improve on the basic SVM and overcome the crucial task of SVM parameter selection.

Unsupervised learning: Unsupervised learning is proving useful to detect incidents that are not well-defined, such as arterial operational problems [41], and secondary crashes or congestion [48] [62]. Yang H. et al. (2017) [48] uses probe car data to identify secondary crashes or non-recurrent congestion. They reduce duplicate reports, or false alarms, by using unsupervised learning via Fuzzy C-Means clustering (i.e. K-Means clustering with Fuzzy logic) to detect the impact area of a primary incident. Finally, they use meta-heuristics optimization (genetic algorithms or Ant-colony optimization) to minimize the boundary of the impact area which could contain secondary crashes or non-recurrent congestion. Anbaroglu et al. (2014) [62] use spatio-temporal clustering to identify significantly large link-journey times across single or adjacent links. Clustering of spatio-temporally overlapping episodes can be used to detect non-recurrent congestion that span multiple links. The CUSUM algorithm detects incidents in arterial roads by applying the CUSUM chart in order to identify incident-based changes in traffic measurements that tend to linger for some time under incident-free conditions. This is an early form of unsupervised learning based anomaly detection for traffic incidents.

Modern forms of unsupervised anomaly detection [63] [64] of incidents use probe car data. Kinoshita et al. (2014) [63] claim that traffic congestion may be a chronic condition in some roadways and may not always be due to incidents. Thus, they attempt to distinguish between incidents and transient congestion in the transportation network by using a probability model with maximum-likelihood parameters and an expectation maximization algorithm. Zhu et al. [64] applied a distance-based outlier mining method in order to identify incidents in arterial roads. They used fluctuations in the travel speed and chose speed differences in nearby sections and adjacent intervals for spatio-temporal analysis.

Arterial operational problems provide yet another form of incidents [41] [47]. Operational problems include detector malfunctioning, signal malfunctioning, lane-blocking incidents, etc. Due to the lack of a well-defined training set for these types of problems, unsupervised learning or other innovative schemes must be used. Khan and Ritchie (1998) [47] use neural network classifiers in a modular architecture.

Lastly, Ren, Jimmy SJ et al. (2012) [65] attempted to improve AID by enhancing the feature representation of incidents via an unsupervised feature learning algorithm which produced higher level features to describe incidents. This allows the use of unlabeled data, or a reduced amount of required labeled data in case of a semi-supervised approach.

8. Secondary Incidents and Non-Recurrent Congestion

Primary Incidents are usually assumed to cause secondary incidents. Hence, detection of an incident could necessitate detection of such incidents [48] [53] [62]. Anbaroglu, B., et al. (2014) [62] present a Non-recurrent congestion (NRC) event detection method using spatio-temporal clustering to detect excessive link-journey times across single/multiple-adjacent link(s). Non-recurrent congestion in adjacent links are clustered together in one episode if they contain at least one common time interval in their duration. A spatio-temporal temporal clustering using overlapping episodes, can be used to detect secondary incidents that span multiple links. The frequency of secondary incidents is directly related to the length of primary incidents [53. They use GPS probe car data to infer the existence of secondary incidents, and then utilize Gaussian Mixture Model (GMM) to determine the reference speed for classification of such events.

9. Data Fusion Techniques

Data fusion is an interdisciplinary method that provides techniques to combine data from several sources in order to achieve synergy with respect to the resultant information derived. The JDL model developed by the U.S. department of Defense is the most popular work on data fusion in general, providing five levels for processing system-level information. In Intelligent Transportation Systems (ITS), each data source brings with it a new challenge. Fixed detectors have low area coverage and accuracy, while probe cars have a low penetration rate, and driver reports are very sparse. However, each new data source also provides us with a new advantage. Since the advancement of road/vehicle telematics, multiple sources of data provide multiple views into traffic conditions. This helps reduce the vagueness and incompleteness characteristic of individual data sources and thereby, allows us to use data fusion in order to augment our interpretation of observed traffic measurements. It is hypothesized that this fusion would result in performance improvement of the incident detection system.

Existing data fusion techniques [73] for ITS applications:

- Bayesian Inference
- Dempster-Shafer evidential theory
- Artificial Neural Networks
- Fuzzy Logic
- Knowledge Based Expert Systems
- Particle Filtering and Kalman/Extended-Kalman Filtering
- Monte Carlo techniques

The earliest works on data fusion for ITS [3] [74] each proposed data fusion frameworks to solve issues in traffic or transportation using travel time estimation and incident detection, respectively. In the case of incomplete data which is insufficient for automatic incident detection, it is recommended to fuse the sensor data or fuse the outputs from incident detection algorithms [75].

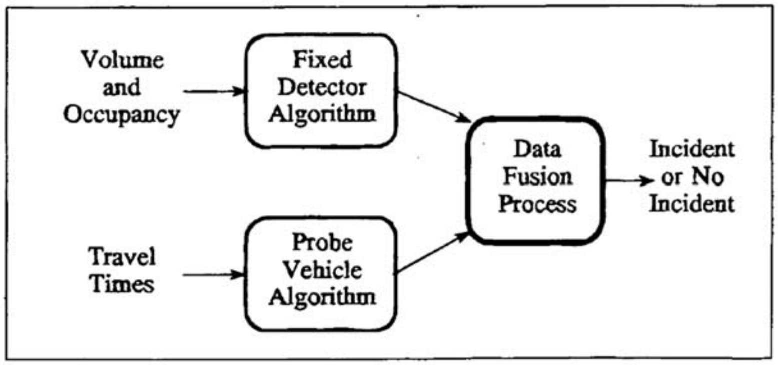

Figure 2: Algorithm output fusion concept (Source: [81])

Sethi et al. (1995) [3], proposed using fixed detector data and probe car data separately in two different algorithms, as part of the ADVANCE ITS, and then used discriminant analysis to estimate incidents. They intended to study how each type of data could complement the other, and concluded that traffic measurements at a particular location were useful for detecting incidents that occurred downstream. They inferred that the fixed detector algorithm performed better than the probe vehicle algorithm, and further observed that the benefit from fixed detector data was dependent on the number of instrumented links in the transportation network, while the benefits of probe car data was limited by reporting rate. Subsequently, they [81] combine the outputs of the two algorithms into a fusion algorithm and develop an AID using surveillance data. Neural Networks were used in two ways: (1) Algorithm Output Fusion which uses neural network to fuse the separate incident-likelihood scores that were output from the fixed detector algorithm and probe vehicle algorithm (Figure 2), and (2) Integrated Fusion which fuses the raw data from both sources and determines the occurrence of an incident. It accomplishes this by combining the functions of fusion and single source algorithms into a single feed-forward neural network. In effect, this integrated fusion attempts to detect incidents by using both data sources simultaneously, but not separately. The raw data consists of

1. volume and occupancy (from fixed detectors)
2. travel time (from probe cars).

The neural network architectures for both fusion algorithms are shown in Figure 3.

The authors show that using data from both sources improved the AID compared to using data from any single source alone. Consequently, they [82] experimented with this idea on the Algorithm Output Fusion module and demonstrated considerable improvements in incident detection. Lastly, they [71] compared the performance of automatic incident detection on signalized arterial streets by fusing data via discriminant analysis and via neural networks. Although they conceded to using driver based reports as an anecdotal data source for manual manipulation of the algorithm, they concluded that neural networks performed better than discriminant analysis.

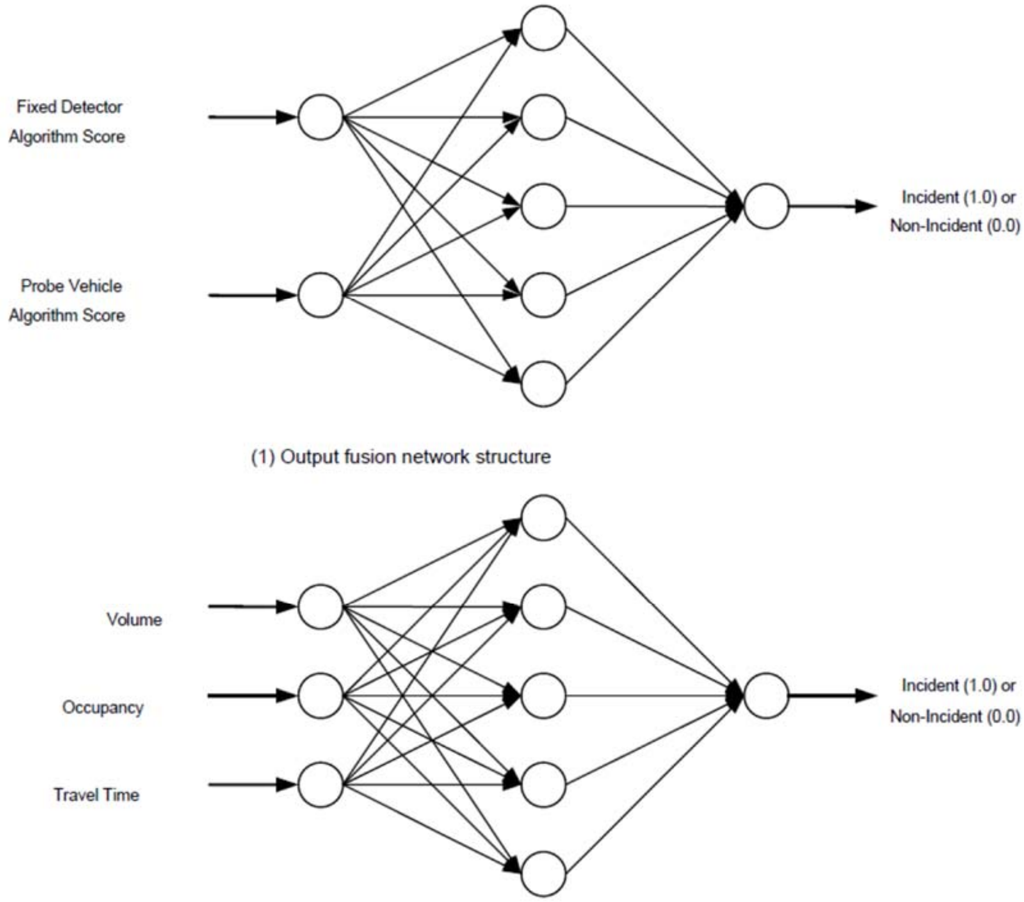

Figure 3: Neural network structures for fusing multiple data types (Source: [2])

With respect to the ADVANCE ITS, Bhandari et al. (1995) [90] also proposed an automatic incident detection system for arterial streets leveraging three separate sources: fixed detector data, probe vehicle data, as well as anecdotal reports. They use three independent modules to pre-process the data from each source separately. The fusion process first uses discriminant analysis to fuse the pre-processed results of fixed detector data and probe car data. Next, the process fuses the resulting output with the output of the anecdotal algorithm, as shown in Figure 4. Hussein & Thomas (2005, 2011) [77] [78] used neural networks to combine simulated loop detector data and simulated probe car data for incident detection on arterials. They compared several neural network architectures by varying probe vehicle penetration rates and detector configurations. Multi-layer feed-forward neural network allowed inclusion of historical data which further improved the results, as did the addition of speed data. Yin et al. (2006) [86] uses toll data for automatic incident detection.

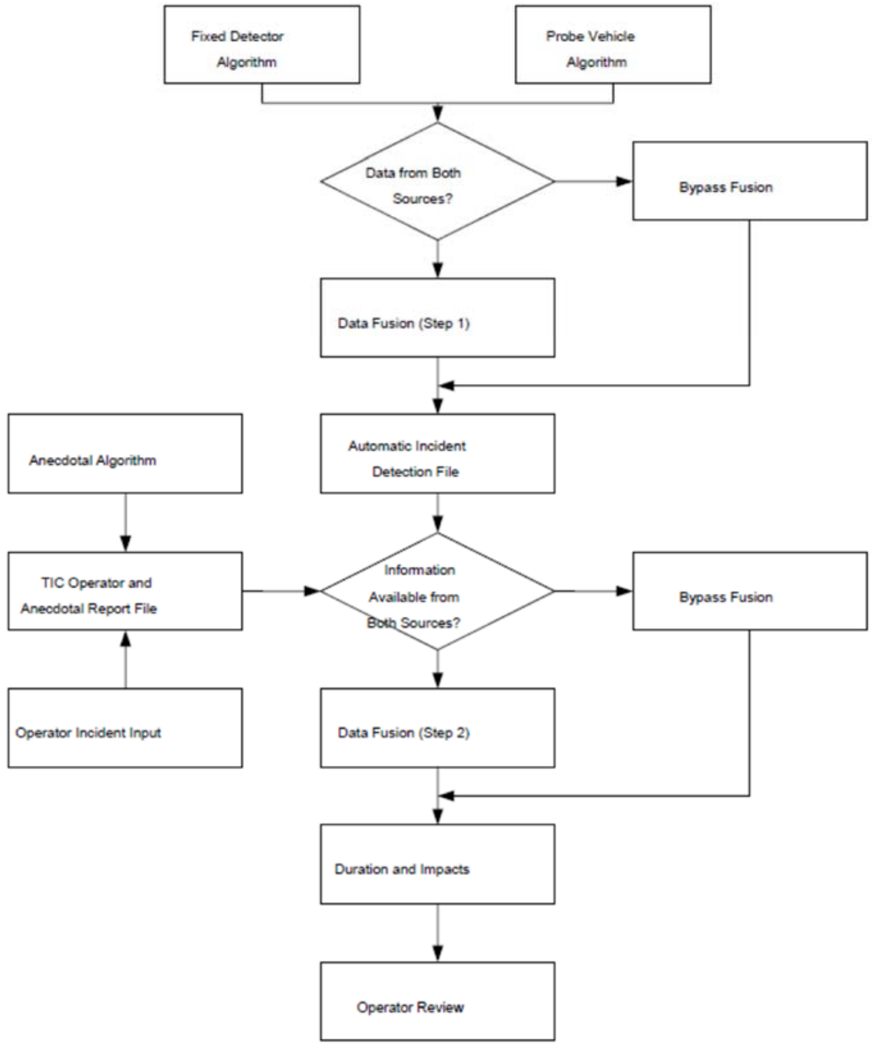

Figure 4: Data fusion system for integration of multiple data sources (Source: [2])

Dempster-Shafer evidential theory is used for data fusion in order to detect incidents as well as other traffic and transportation events [83] [84] [85]. Byun et al. (1999) [85] attempts to solve traffic congestion problems in links having limited capacity by assigning weights to incident reports, thereby identifying true incidents and false incidents, i.e. possible false alarms. They run an incident detection algorithm on three data sources separately: loop detectors, CCD cameras, and Probe Vehicles. Dempster-Shafer's algorithm is used to fuse the three results and increase the accuracy of traffic-condition reports. Klein et al. (2000, 2002) [83][84] uses Dempster-Shafer's algorithm to combine data from three different sources in order to detect and verify incidents and other traffic events, especially when the individual data sources cannot determine the occurrence of an event with full confidence. The author provides an example where all available data is combined using Dempster-Shafer's rule allowing them to distinguish the most probable event. Zeng et al. (2008) [87] claim that raw data from individual sources may be corrupted with unexpected missing values. They demonstrate creating an SVM classifier for each of three different sources of traffic data: loop inductive detector, AVI (automated vehicle identification) observation and floating car data (FCD). They use Dempster-Shafer's evidence theory to combine the multiple SVM-classifiers.

Bayesian inference has been used to detect incidents via a multiple-attributes decision-making view. Thomas (1996) [79] combined occupancies and volumes reported by induction loop detectors along with probe car data. Observations showed that algorithms based on fixed-detector data performed well. While probe car data alone suffered from an excess of overlaps in class distributions, it complemented fixed-detector data quite well. Next, Thomas (1998) [80] proposed an incident detection approach based on two characteristics: 1) We can classify arterial traffic into several states based on the type of sensor (fixed detectors or probe-cars); and 2) We must use a multi-variable vector (as opposed to a scalar) as the discrimination criterion for an incident. The algorithm was tested using data from a modified INTRAS simulation. The types of data included probe car travel time, number of probe reports, lane specific detector occupancies and vehicle counts. This approach uses multivariate classifiers to distinguish multiple traffic states on arterials.

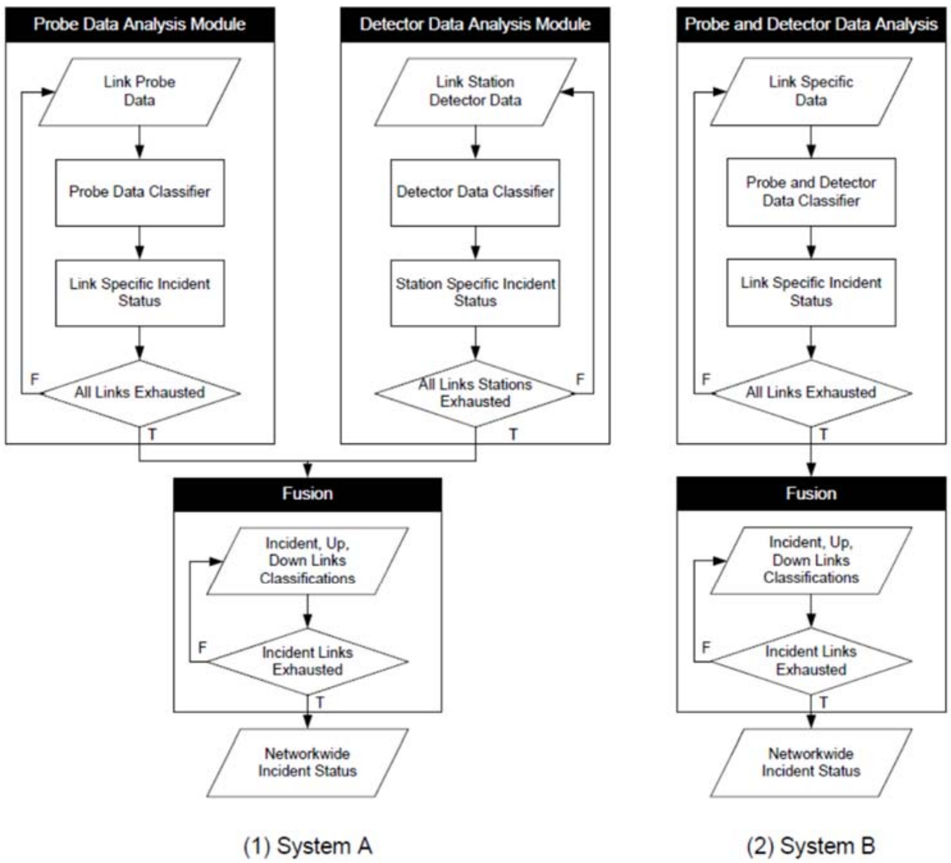

Figure 5: Arterial incident detection systems using multiple sensors and multiple states (Source: [2])

Thomas (1998) [80] proposed two types of system configurations shown in Figure 5. System *A* processes spot detector data and spatial travel times on the link-level. System *B* uses probe data and spatial data on the link-level by preprocessing spot detector data. The results demonstrate that the supplementation of probe data enhances the performance of detector-based algorithms.

Cohen (2003) [76] uses three schemes to fuse the output of multiple incident detection algorithms. He used logical aggregation, neural network fusion, and a veto procedure. His validation step uses real-world data and demonstrates that the logical aggregation and veto procedure results in considerable performance improvement when compared to any single source detection algorithm alone. Westerman et al. (1996) [88] performs incident detection and estimates travel-time by allowing a loop detector algorithm and a probe data algorithm to operate separately, while simultaneously complementing each other. Their algorithms use two stages (see Figure 6).

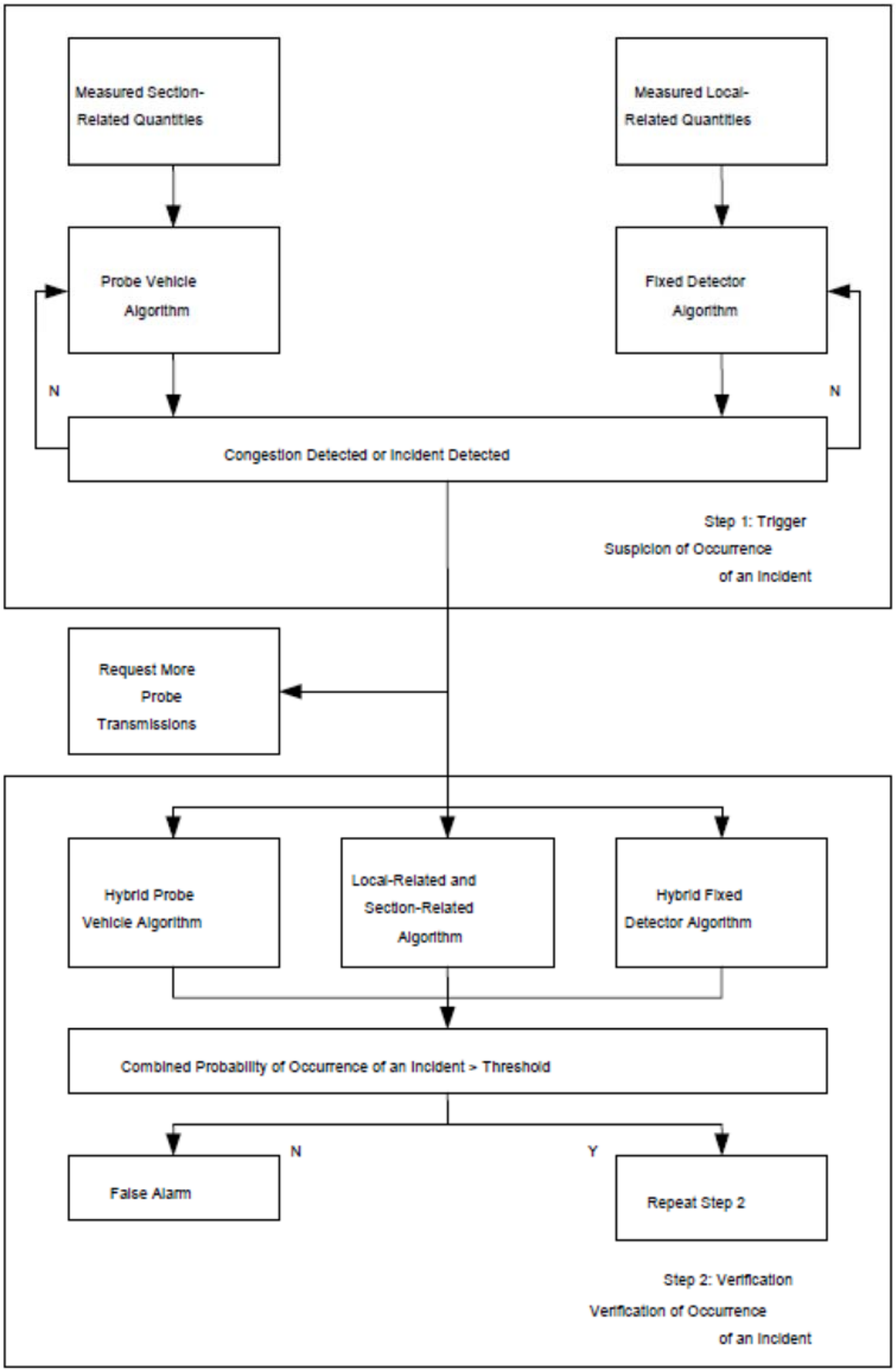

Figure 6: A compound loop detector and probe vehicle AID (Source: [2])

The two stages of the algorithms [88] in Figure 6 are as follows:

1. a trigger stage which suggests the occurrence of an incident,
2. a verification stage that automatically verifies the occurrence.

The probabilities of the incident's occurrence from each algorithm are combined using a weight averaging fusion method in order to reach a final classification decision in the verification stage.

The weight of each component is determined by the number of verification steps that were executed. Dub-STAR [89] merges the traditional data sources, like loop detectors and traffic cameras, with social media and SMS messages in order to provide insights into real-time traffic conditions and incidents.

10. Conclusions

- Minimizing the boundary of the possible-region containing the incident before executing the detection algorithm could reduce performance-time and may increase accuracy. It could also reduce false alarms. Optimization heuristics can be used for this purpose [48] [68].
- In probe vehicles, it is not recommended to use the statistical-difference between mean travel-times of multiple probe vehicles, and act when the mean travel-time crosses some defined threshold. This technique requires a large penetration rate for good results (i.e. > 50% probes) [3] [58] [59]. However, the required penetration rate may be reduced by using optimization heuristics.
- Spatio-Temporal analysis, i.e. considering Space and Time dimensions, could lower False Alarm Rates (FAR) in AID algorithms [32] [52] [62] [64] [69].
- For anomaly detection, model a stable state for the road's traffic before detecting anomalies against that stable state [63].
- Use Ant Colony algorithm, or other meta-heuristic optimizations to enhance the performance of a Machine Learning approach [7] [48].
- Fuzzy Logic along with Machine Learning techniques can minimize error due to uncertainty in data-points. [13] [48]
- Selection of the Machine Learning model's parameters should be prioritized as one of the critical steps in the design of the solution [7] [13] [16] [61].
- Support Vector Machine (SVM) can produce non-linear classifiers with high-dimensionality. However, SVM requires careful selection of parameters [7] [61].
- Unsupervised learning is valuable in detecting events that have no concrete definitions, such as arterial operation problems [41] [47], congestion and secondary incidents [48] [62], etc.
- No fusion method always performs better than the other. Instead, each fusion method excels with data from a particular set of sensor types.

11. References

1. Williams, Billy M., and Angshuman Guin. "Traffic management center use of incident detection algorithms: Findings of a nationwide survey." *IEEE Transactions on intelligent transportation systems* 8, no. 2 (2007): 351-358.
2. Parkany, Emily, and Chi Xie. A complete review of incident detection algorithms & their deployment: what works and what doesn't. No. NETCR 37, NETC 00-7. 2005.
3. Sethi V., Bhandari, N., Koppelman, F.S., Schofer, J.L., 1995. Arterial incident detection using fixed detector and probe vehicle data. Transp.Res. Part C 3 (2), 99–112.
4. P. Roy and B. Abdulhai, “GAID: Genetic adaptive incident detection for freeways,” presented at the TRB 82nd Annu. Meeting, Washington, DC, 2003. Preprint (CD-ROM) # 001201.
5. Liu, Qingchao, Jian Lu, Shuyan Chen, and Kangjia Zhao. "Multiple Naïve Bayes Classifiers Ensemble for Traffic Incident Detection." Mathematical Problems in Engineering 2014 (2014).
6. Chen, S., Wang, W., & Van Zuylen, H. (2009). Construct support vector machine ensemble to detect traffic incident. Expert systems with applications, 36(8), 10976-10986.
7. Liang, G. (2015). Automatic Traffic Accident Detection Based on the Internet of Things and Support Vector Machine. International Journal of Smart Home (IJSH), 9(4), 97-106.
8. Xiao, J., & Liu, Y. (2012). Traffic incident detection using multiple-kernel support vector machine. Transportation Research Record: Journal of the Transportation Research Board, (2324), 44-52.
9. H. Dia and G. Rose, “Development and evaluation of neural network freeway incident detection models using field data,” Transp. Res. Part C, vol. 1, no. 3, pp. 203–217, 1997.
10. Cheu, R. L., & Ritchie, S. G. (1995). Automated detection of lane-blocking freeway incidents using artificial neural networks. Transportation Research Part C: Emerging Technologies, 3(6), 371-388.
11. Long Cheu, R., Srinivasan, D., & Hoon Loo, W. (2004). Training neural networks to detect freeway incidents by using particle swarm optimization. Transportation Research Record: Journal of the Transportation Research Board, (1867), 11-18
12. Zhang, Z., He, Q., Gao, J., & Ni, M. (2018). A deep learning approach for detecting traffic accidents from social media data. Transportation Research Part C: Emerging Technologies.
13. El Hatri, C., & Boumhidi, J. (2017). Fuzzy deep learning based urban traffic incident detection. Cognitive Systems Research.
14. Hawas, Y. E. (2007). A fuzzy-based system for incident detection in urban street networks. Transportation Research Part C: Emerging Technologies, 15(2), 69-95.
15. A. Samant and H. Adeli, “Feature extraction for traffic incident detection using wavelet transform and linear discriminant analysis,” Comput.-Aided Civil Infrastruct. Eng., vol. 15, no. 4, pp. 241–250, 2000.
16. Jeong, Y. S., Castro-Neto, M., Jeong, M. K., & Han, L. D. (2011). A wavelet-based freeway incident detection algorithm with adapting threshold parameters. Transportation Research Part C: Emerging Technologies, 19(1), 1-19.
17. Teng, H., & Qi, Y. (2003). Application of wavelet technique to freeway incident detection. Transportation Research Part C: Emerging Technologies, 11(3-4), 289-308.
18. D'Andrea, E., & Marcelloni, F. (2017). Detection of traffic congestion and incidents from GPS trace analysis. Expert Systems with Applications, 73, 43-56.
19. C. L. Dudek, C. J. Messer, and N. B. Nuckles, “Incident detection on urban freeways,” in Transp. Res. Rec. 495. Washington, DC: TRB, Nat. Res. Council, 1974, pp. 12–24.

20. H. J. Payne, “Freeway incident detection based upon pattern classification,” in Proc. IEEE Conf. Decision Control Including 14th Symp. Adaptive Processes, 1975, pp. 688–692.
21. H. J. Payne and S. C. Tignor, “Freeway incident detection algorithms based on decision trees with states,” in Transp. Res. Rec. 682. Washington, DC: TRB, Nat. Res. Council, 1978, pp. 30–37.
22. Levin, M. and Krause, G.M. (1978). “Incident detection: a Bayesian approach.” Transportation Research Record, No. 682, TRB, National Research Council, pp. 52-58.
23. Tsai, J. and Case, E.R. (1979). “Development of freeway incident detection algorithms by using pattern recognition techniques.” Transportation Research Record, No. 722, TRB, National Research Council, pp. 113-116.
24. S. A. Ahmed and A. R. Cook, “Time series models for freeway incident detection,” ASCE Transp. Eng. J., vol. 106, no. 6, pp. 731–745, Nov. 1980.
25. Cook, A.R. and Cleveland, D.E. (1974). “Detection of freeway capacity-reducing incidents by traffic stream measurements.” Transportation Research Record, No. 495, TRB, National Research Council, pp. 1-11.
26. Stephanedes, Y.J., Chassiakos, A.P. and Michalopoulos, P.G. (1992). “Comparative performance evaluation of incident detection algorithms.” Transportation Research Record, No. 1360, TRB, National Research Council, pp. 50-57
27. Willsky, A.S., Chow, E.Y., Gershwin, S.B., Greene, C.S., Houpt, P. and Kurkjian, A.L. (1980). “*Dynamic model-based techniques for the detection of incidents on freeways*.” IEEE Transactions on Automatic Control, Vol. 25, No. 3, pp. 347-360.
28. A. I. Gall and F. L. Hall, “Distinguishing between incident congestion and recurrent congestion: A
    a. proposed logic,” in *Transp. Res. Rec. 1232*. Washington, DC: TRB, Nat. Res. Council, 1989, pp. 1– 8.
29. Michalopoulos, P.G. (1991). “*Vehicle detection video through image processing: the Autoscope system.*” IEEE Transactions on Vehicular Technology, Vol. 40, No. 1, IEEE, pp. 21-29.
30. Michalopoulos, P.G., Jacobson, R.D., Anderson, C.A. and DeBruycker, T.B. (1993). “*Automatic incident detection through video image processing.*” Traffic Engineering and Control, Vol. 34, No. 2, pp. 66-75.
31. Parkany, E. and Bernstein, D. (1995). “Design of incident detection algorithms using vehicle-to-roadside communication sensors.” Transportation Research Record, No. 1494, TRB, National Research Council, pp. 67-74.
32. Sermons, M.W. and Koppelman, F.S. (1996). “Use of vehicle positioning data for arterial incident detection.” Transportation Research Part C, Vol. 4, No. 2, pp. 87-96.
33. Balke, K., Dudek, C.L. and Mountain, C.E. (1996). “Using probe-measured travel time to detect major freeway incidents in Houston, Texas.” Transportation Research Record, No. 1554, TRB, National Research Council, pp. 213-220.
34. Petty, K. F., Skabardonis, A. and Varaiya, P. P. (1997). “Incident detection with probe vehicles: performance, infrastructure requirements and feasibility.” Transportation Systems 1997: A Proceedings Volume from the 8th IFAC/IFIP/IFORS Symposium, Chania, Greece, June 16-18, 1997, Vol. 1, pp. 125-130.
35. Mouskos, K.C., Niver, E., Lee, S., Batz, T. and Dwyer, P. (1999). “Transportation operation coordinating committee system for managing incidents and traffic: evaluation of the incident detection system.” Transportation Research Record, No. 1679, TRB, National Research Council, pp. 50-57.
36. Niver, E., Mouskos, K.C., Batz, T. and Dwyer, P. (2000). “Evaluation of the TRANSCOM’s system for managing incidents and traffic (TRANSMIT).” IEEE Transactions on Intelligent Transportation Systems, Institute of Electrical and Electronics Engineers, Vol. 1, No. 1, pp. 15-31.
37. Hellinga, B. and Knapp, G. (2000). “Automatic vehicle identification technology-based freeway incident detection.” Transportation Research Record, No. 1727, TRB, National Research Council, pp. 142-153.

38. Payne, H. J. Development and testing of incident detection algorithms, Volume 1: summary of results. No. FHWA-RD-76-19 Final Rpt. 1976.
39. Lin, Wei-Hua, and Carlos F. Daganzo. "A simple detection scheme for delay-inducing freeway incidents." Transportation Research Part A: Policy and Practice 31, no. 2 (1997): 141-155
40. Thancanamootoo, S., and Matthew GH Bell. "Automatic detection of traffic incidents on a signal-controlled road network." Research Report 76 (1988).
41. Han, Lee D., and Adolf Darlington May. Automatic detection of traffic operational problems on urban arterials. No. 9-15. 1989.
42. Lee, Jung-Taek, and William C. Taylor. "Application of a dynamic model for arterial street incident detection." Journal of Intelligent Transportation Systems 5, no. 1 (1999): 53-70.
43. Chen, Chao-Hua, and Gang-Len Chang. "A dynamic real-time incident detection system for urban arterials—system architecture and preliminary results." In Pacific Rim TransTech Conference: Volume I: Advanced Technologies, pp. 98-104. ASCE, 1993.
44. Jeong, Young-Seon, Manoel Castro-Neto, Myong K. Jeong, and Lee D. Han. "A wavelet-based freeway incident detection algorithm with adapting threshold parameters." Transportation Research Part C: Emerging Technologies 19, no. 1 (2011): 1-19.
45. Teng, Hualiang, and Yi Qi. "Application of wavelet technique to freeway incident detection." Transportation Research Part C: Emerging Technologies 11, no. 3-4 (2003): 289-308.
46. Asare, Sampson Kwasi, Yaw Adu-Gyamfi, Nii Attoh-Okine, and Hyungjun Park. "Adaptive freeway incident detection algorithm using the Hilbert-Huang transform." In 92nd Annual Meeting of the Transportation Research Board, Washington, DC. 2013.
47. Khan, Sarosh I., and Stephen G. Ritchie. "Statistical and neural classifiers to detect traffic operational problems on urban arterials." Transportation Research Part C: Emerging Technologies 6, no. 5-6 (1998): 291-314.
48. Yang, Hong, Zhenyu Wang, Kun Xie, and Dong Dai. "Use of ubiquitous probe vehicle data for identifying secondary crashes." Transportation research part C: emerging technologies 82 (2017): 138-160.
49. Lee, Sibok, Raymond A. Krammes, and John Yen. "Fuzzy-logic-based incident detection for signalized diamond interchanges." Transportation Research Part C: Emerging Technologies 6, no. 5-6 (1998): 359-377.
50. Chang, E. C. P., & Wang, S. H. (1994). Improved freeway incident detection using fuzzy set theory (No. 1453).
51. Hawas, Y. E. (2007). A fuzzy-based system for incident detection in urban street networks. Transportation Research Part C: Emerging Technologies, 15(2), 69-95.
52. El Hatri, C., & Boumhidi, J. (2017). Fuzzy deep learning based urban traffic incident detection. Cognitive Systems Research.
53. Park, Hyoshin, and Ali Haghani. "Real-time prediction of secondary incident occurrences using vehicle probe data." Transportation Research Part C: Emerging Technologies 70 (2016): 69-85.
54. Skabardonis, Alexander, Ted Chira-Chavala, and Daniel Rydzewski. "The I-880 field experiment: effectiveness of incident detection using cellular phones." (1998).
55. Walters, Carol H., Poonam B. Wiles, and Scott A. Cooner. "Incident detection primarily by cellular phones: an evaluation of a system for dallas." In The 78th TRB Annual Meeting, Washington, DC, America. 1999.
56. Mussa, Renatus N., and Jonathan E. Upchurch. "Simulation assessment of incident detection by cellular phone call-in programs." Transportation 26, no. 4 (1999): 399-416.
57. Mussa, Renatus, and J. Upchurch. "Modeling incident detection using vehicle-to-roadside communications systems." In Journal of the transportation research forum, vol. 39, no. 4, pp.117-127. Transportation Research Forum, 2000.
58. Li, Yanying, and Mike McDonald. "Motorway incident detection using probe vehicles." In Proceedings of the Institution of Civil Engineers-Transport, vol. 158, no. 1, pp. 11-15. Thomas Telford Ltd, 2005.
59. Long Cheu, Ruey, Hongtu Qi, and Der-Horng Lee. "Mobile sensor and sample-based algorithm for freeway incident detection." Transportation Research Record: Journal of the Transportation Research Board 1811 (2002): 12-20.

60. Yuan, Fang, and Ruey Long Cheu. "Incident detection using support vector machines." Transportation Research Part C: Emerging Technologies 11, no. 3-4 (2003): 309-328.
61. Chen, Shuyan, Wei Wang, and Henk Van Zuylen. "Construct support vector machine ensemble to detect traffic incident." Expert systems with applications 36, no. 8 (2009): 10976-10986.
62. Anbaroglu, Berk, Benjamin Heydecker, and Tao Cheng. "Spatio-temporal clustering for non-recurrent traffic congestion detection on urban road networks." Transportation Research Part C: Emerging Technologies 48 (2014): 47-65.
63. Kinoshita, Akira, Atsuhiro Takasu, and Jun Adachi. "Traffic Incident Detection Using Probabilistic Topic Model." In EDBT/ICDT Workshops, pp. 323-330. 2014.
64. Zhu, Tongyu, Jifang Wang, and Weifeng Lv. "Outlier mining based automatic incident detection on urban arterial road." In Proceedings of the 6th International Conference on Mobile Technology, Application & Systems, p. 29. ACM, 2009.
65. Ren, Jimmy SJ, Wei Wang, Jiawei Wang, and Stephen Liao. "An unsupervised feature learning approach to improve automatic incident detection." In Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on, pp. 172-177. IEEE, 2012.
66. Gu, Yiming, Zhen Sean Qian, and Feng Chen. "From Twitter to detector: Real-time traffic incident detection using social media data." Transportation research part C: emerging technologies 67(2016): 321-342.
67. Zhang, Zhenhua, Qing He, Jing Gao, and Ming Ni. "A deep learning approach for detecting traffic accidents from social media data." Transportation Research Part C: Emerging Technologies 86 (2018): 580-596.
68. Kamran, Shoaib, and Olivier Haas. "A multilevel traffic incidents detection approach: Identifying traffic patterns and vehicle behaviours using real-time gps data." In Intelligent vehicles symposium, 2007 IEEE, pp. 912-917. IEEE, 2007.
69. D'Andrea, Eleonora, and Francesco Marcelloni. "Detection of traffic congestion and incidents from GPS trace analysis." Expert Systems with Applications 73 (2017): 43-56.
70. Lingras, P. & Adamo, M. (1996), Average and peak trafficvolumes: Neural nets, regression, and factor approaches, Jour-nal of Computing in Civil Engineering, ASCE, 10 (4), 300–6.
71. Ivan, John N., and Vaneet Sethi. "Data fusion of fixed detector and probe vehicle data for incident detection." Computer-Aided Civil and Infrastructure Engineering 13, no. 5 (1998): 329-337.
72. Jin, Xin, Ruey Long Cheu, and Dipti Srinivasan. "Development and adaptation of constructive probabilistic neural network in freeway incident detection." Transportation Research Part C: Emerging Technologies 10, no. 2 (2002): 121-147.
73. El Faouzi, Nour-Eddin, and Lawrence A. Klein. "Data fusion for ITS: techniques and research needs." Transportation Research Procedia 15 (2016): 495-512.
74. El Faouzi, N. E., and J. B. Lesort. Travel time estimation on urban networks from traffic data and on-board trip characteristics. No. Volume 1. 1995.
75. Mahmassani, Hani S., Carl Haas, Sam Zhou, and Josh Peterman. "Evaluation of incident detection methodologies." Work (1795): 1.
76. Cohen, S. "Fusion of incident detection algorithms." In Proceedings of the Multisource Data Fusion in Traffic Engineering Workshop, vol. 87, pp. 109-117. 2003.
77. Thomas, Kim, and Hussein Dia. "Neural network incident detection on arterials using fusion of simulated probe vehicle and loop detector data." In Proceedings of the 12th ITS World Congress, San Francisco, California, pp. 1-12. 2005.
78. Dia, Hussein, and Kim Thomas. "Development and evaluation of arterial incident detection models using fusion of simulated probe vehicle and loop detector data." Information Fusion 12, no. 1 (2011): 20-27.
79. Thomas, Nigel. "Multi sensor, multivariate, and multi-class incident detection system for arterial streets." Transportation and traffic theory 13 (1996): 315-339.
80. Thomas, N. E. "Multi-state and multi-sensor incident detection systems for arterial streets." Transportation Research Part C: Emerging Technologies 6, no. 5-6 (1998): 337-357.
81. Ivan, John N., Joseph L. Schofer, Frank S. Koppelman, and Lina LE Massone. "Real-time data fusion for arterial street incident detection using neural networks." Transportation Research Record 1497 (1995): 27-35.

82. Ivan, John N. "Neural network representations for arterial street incident detection data fusion." Transportation Research Part C: Emerging Technologies 5, no. 3-4 (1997): 245-254.
83. Klein, Lawrence A. "Dempster-Shafer data fusion at the traffic management center." In Transportation Research Board 79th Annual Meeting. 2000.
84. Klein, Lawrence, Ping Yi, and Hualiang Teng. "Decision support system for advanced traffic management through data fusion." Transportation Research Record: Journal of the Transportation Research Board 1804 (2002): 173-178.
85. Byun, S. C., D. B. Choi, B. H. Ahn, and Hanseok Ko. "Traffic incident detection using evidential reasoning based data fusion." In Proceedings of 6th World Congress on Intelligent Transport Systems (ITS), Toronto, Canada, November 8-12, 1999.
86. Yin, Xiangyuan, Weiming Liu, and Liping Guan. "Research on automatic incident detection algorithm based on fusion of freeway mainline information and toll collection information." In Systems, Man and Cybernetics, 2006. SMC'06. IEEE International Conference on, vol. 4, pp. 2915-2919. IEEE, 2006.
87. Zeng, Dehuai, Jianmin Xu, and Gang Xu. "Data fusion for traffic incident detection using DS evidence theory with probabilistic SVMs." Journal of computers 3, no. 10 (2008): 36-43.
88. Westerman, Marcel, Remco Litjens, and Jean-Paul Linnartz. "Integration of probe vehicle and induction loop data: Estimation of travel times and automatic incident detection." (1996).
89. Daly, Elizabeth M., Freddy Lecue, and Veli Bicer. "Westland row why so slow?: fusing social media and linked data sources for understanding real-time traffic conditions." In Proceedings of the 2013 international conference on Intelligent user interfaces, pp. 203-212. ACM, 2013.
90. Bhandari, Nikhil, Frank S. Koppelman, Joseph L. Schofer, Vaneet Sethi, and John N. Ivan. "Arterial incident detection integrating data from multiple sources." Transportation research record (1995): 60-69.