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16. ABSTRACT

This report provides a synthesis of Automated Video Incident Detection (AVID) systems as well as a range of other technologies available for Automated Incident Detection (AID) and more general traffic system monitoring. In this synthesis, we consider the impacts of big data and machine learning techniques being introduced due to the accelerating pace of ubiquitous computing in general and Connected and Automated Vehicle (CAV) development in particular.

We begin with a general background on the history of traffic management. This is followed by a more detailed review of the incident management process to introduce the importance of incident detection and general situational awareness in the Traffic Management Center (TMC). We then turn our attention to AID in general and AVID in particular before discussing the implications of more recent data sources for AID that have seen limited deployment in production systems but offer significant potential. Finally, we consider the changing role of the TMC and how new data can be integrated into traffic management processes most effectively.

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Situational Awareness for Transportation Management

Automated Video Incident Detection and Other Machine Learning Technologies for the TMC

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Terminology

AI	Artificial Intelligence
AID	Automated Incident Detection
ANN	Artificial Neural Network
ARC-IT	Architecture Reference for Cooperative and Intelligent Transportation
ATMS	Advanced Transportation Management Systems
AVID	Automated Video Incident Detection
BNN	Bayesian Neural Network
BSM	Basic Safety Message
CAV	Connected Autonomous Vehicle
Caltrans	California Department of Transportation
CCTV	Closed Circuit Television
CHP	California Highway Patrol
CMS	Changeable Message Signs
CTMLabs	Calfornia Traffic Management Laboratories
CVRIA	Connected Vehicle Reference Implementation Architecture
C-V2X	Cellular V2X
DF	Data Fusion
DR	Detection Rate
DSRC	Dedicated Short Range Communications
FAR	False Alarm Rate
FCD	Floating Car Data
FSP	Freeway Service Patrol
GPS	Global Positioning System
ICT	Information and Communications Technology
ILD	Inductive Loop Detector
IoT	Internet of Things
ISP	Information Service Provider
ISTEA	Intermodal Surface Transportation Efficiency Act
ITS	Intelligent Transportation Systems
IVHS	Intelligent Vehicle Highway Systems
LOS	Level-of-Service
MCR	Misclassification Rate
MTTD	Mean Time-To-Detect
NITSA	National ITS Architecture
PeMS	Caltrans Performance Monitoring System
PNN	Probabilistic Neural Network
TMC	Traffic Management Center
TMT	Traffic Management Team
UAV	Unmanned Aerial Vehicle
VA	Video Analytics
VANET	Vehicular Ad-hoc NETwork
VDAS	Vehicle Detection Application System

DISCLAIMER

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1 Introduction

Traffic incident management is an active process involving coordination between multiple agencies and field operations teams ranging from emergency services to maintenance. In large agencies, such as Caltrans districts, this process is coordinated by the Traffic Management Center (TMC). Prior research has demonstrated the importance of early verification of incidents for reducing the delays associated with capacity-reducing events. The total delay caused by an incident is at least proportional, if not polynomially related, to the time required to verify a given incident (Rindt et al., 2010). Generally, this is due to the fact that a response to an event cannot be deployed until the problem is diagnosed, leading to significantly greater queuing and thus increased delays and impacts to system safety. Once an incident is diagnosed through verification, the response process can be well organized and more deterministic. As a result, shortening the verification time is a critical component in the efficient management of incidents. Because the above steps are sequential, early verification is ultimately dependent upon early identification of a disruption.

In California, the identification of incidents arrives through a variety of channels including the California Highway Patrol's (CHP) iCAD system, telephone reports from the public, and the Caltrans Closed Circuit Television (CCTV) system. The first two of these channels are particularly effective for reporting of severe incidents, when emergency phone calls are made in response to accidents. Less severe events, such as stalled vehicles or debris in the roadway have less likelihood of being quickly reported by the public. While these situations tend to produce less severe disruptions to traffic flow, they create conditions that are more likely to produce secondary incidents that may have significantly greater severity. At the same time, active monitoring of every stretch of roadway by a TMC operator is time consuming, tedious, and a generally inefficient use of human resources.

The past several decades have seen the development a wide variety of Automated Incident Detection (AID) methods ranging from the theoretical to practical deployments. These efforts have produced an equally wide variety of results, but generally there is enough promise in these methods to suggest they may aid TMC operators in improving incident identification time. This, in turn, improves response times to a variety of system events, reduces the occurrence of secondary incidents, and generally improves the efficiency of TMC operations.

This project was conceived to perform an evaluation of candidate Vehicle Detection Application System (VDAS) for performing Video Analytics (VA) and Automated Video Incident Detection (AVID) and generally characterize traffic conditions, identify incidents, and improve incident identification and response times. Our experience working with TMC operations suggests that TMC operators tend to have developed a level of efficiency with existing processes such that the introduction of new tools and techniques—no matter the technical potential—can actually disrupt existing processes leading to less efficiency overall. Thus, an additional focus was to consider how these AVID systems can be directly integrated into existing TMC processes with a minimum of disruption.

2 Summary of Work Performed

The original scope of work involved three primary tasks:

1. **Literature Search**: review commercial VDASs along with any recent deployments or evaluations that might inform this effort;

2. **AVID Tool Evaluation**: evaluate candidate commercial AVID systems to establish their performance capabilities given the constraints of Caltrans infrastructure; and

3. **Real-time pilot study**: using a selected VDAS based upon the tool evaluation, demonstrate how VA and AVID can be integrated into TMC processes.

The broad intent of the effort was to evaluate the impact this system has on the measured delays of particular classes of incidents over time. The research plan assumed the availability of the resources and direct CCTV and communications links provided by the Calfornia Traffic Management Laboratories to collect system data post-installation and the use of the Caltrans TMC performance evaluation system (Rindt et al., 2010) to determine the effectiveness of AVID in incident response.

However, during the course of the project, a number of issues disrupted this planned scope of work. The most serious was the unexpected discontinuation of the Calfornia Traffic Management Laboratories at UC Irvine. The original proposal was built around leveraging the capabilities of CTMLabs, which included the ability to control and capture Caltrans District 12 CCTV feeds making laboratory analysis readily feasible. The loss of CTMLabs functionality meant that the communications and computing infrastructure upon which task 2 experiments were intended to be carried out was no longer available. Then, soon after the start of the project, Caltrans District 12 began significant upgrades to their TMC and CCTV infrastructure. Further, the agreements open which CTMLabs allowed for tight technical coordination—and specifically the integration of research-developed software products—between UCI and Caltrans District 12 TMC were no longer available. This brought into question the ability to conduct a real-time pilot study during which

VDAS outputs would be integrated into TMC operations through software modifications to TMC systems.

Due to these modifications, the research team concluded that a live TMC evaluation was not feasible and agreed to attempt to collect and test candidate VDAS systems using pre-recorded video from existing Caltrans CCTV feeds over the now unsupported CTMLabs communications intertie between Caltrans District 12 and UCI. The research team was able to access a web-based interface for four video streams from District 12 over the intertie. To achieve this goal, it was necessary to reverse engineer the custom web software delivering the feeds to save the streams for subsequent analysis. Unfortunately, the amount of video saved from the four feeds proved to be both time-limited and low quality due to the intermittent connectivity provided over the legacy intertie and web interface. The VDAS tool evaluation was primarily intended to test the ability of AVID systems to identify disabled vehicles and/or debris in roadway—scenarios that demand the analysis of many hours of video to identify candidate events. As a result, the limited quality and amount of video collected over the intertie produced no quality candidates representing these test scenarios.

Without a concrete set of video data to evaluate, the AVID tool evaluation using District 12 video became infeasible. This, along with the loss of the CTMLabs, made it impossible to carry out the pilot study. As a result, the scope of the project was modified to focus on an expansion of the literature review into a synthesis of not only AVID systems, but to consider the range of technologies available for AID and system monitoring. In this synthesis, we consider the impacts of big data and machine learning techniques being introduced due to the accelerating pace of ubiquitous computing in general and Connected Autonomous Vehicle (CAV) development in particular.

We begin with a general background on the history of traffic management in Section 3. This is followed by a more detailed review Section 4 of the general incident management process to introduce the importance of incident detection and general situational awareness in the TMC. We then turn our attention to AID in general (Section 6) and AVID in particular (Section 7). In section Section 8 we discuss more recent data sources for AID that have seen limited deployment in production systems but offer significant potential. We then consider the changing role of the TMC and how new data can be integrated into TMC processes most effectively (Section 9) before concluding in Section 10.

3 Background

The last great shift in transportation norms in the United States occurred during the postwar period as the sustained period of economic growth and development led to the explosion of car ownership and the development of the Interstate Highway System. The rising importance of the automobile led to the establishment of the United States Department of Transportation in 1966 and the concomitant development of national standards for safety and roadway operations. During this period, the first notions of using advanced technologies to improve traffic safety and operations arose (Auer et al., 2016).

With the establishment of its first TMC in Los Angeles in 1971 (Caltrans, 2017a), the State of California ushered in the current era of traffic management. This began with the widespread deployment of a broad range of traffic monitoring and management technologies ranging from monitoring technologies such as Inductive Loop Detector (ILD) and CCTV to control strategies such as on-ramp management through metering and information provision through Changeable Message Signs (CMS). During the 1980s, researchers and agencies began to focus on developing automated systems for managing traffic flow on both freeways and arterials, particularly as Information and Communications Technology (ICT) continued its steady advancement.

Realizing the potential provided by these new technologies, the passage of the Intermodal Surface Transportation Efficiency Act (ISTEA) in 1991 established research, development, and deployment programs that laid the groundwork for the transportation revolution that today appears imminent. In particular, the Intelligent Vehicle Highway Systems (IVHS) program—later renamed to the Intelligent Transportation Systems (ITS) program—seeded the development of ideas and technologies for the creation of smarter infrastructure. This led to the creation of the National ITS Architecture (NITSA), which has seen ongoing development of a set of standards for how the transportation system can adapt to and integrate changes in ICT (Iteris, Inc., 1998). While the terminology may have changed, the fundamental concepts have seen a steady evolution and the resulting initiatives have moved transportation in the United States to the cusp of the CAV revolution, whereby fleets of driverless vehicles will provide shared mobility services to the population with potentially unprecedented levels of efficiency and safety that will touch virtually every sector of the economy.

In the synthesis that follows, we focus on the problem of creating situational awareness of freeway operations through traffic state monitoring and AID systems, keeping in mind the broader context of traffic management. After a review of incident management processes, we provide an overview of incident detection methods before focusing on AVID systems, including their development as well as historical and modern deployments. We follow this discussion with a look at competing and/or complementary AID alternatives made possible by advances in computing, machine learning, and ICT, including the highly promising incorporation of CAV data into the incident management infrastructure.

4 Incident Management

The primary TMC function of interest for this review is the management of freeway incidents. For our purposes, such incidents are disruptions to the normal demand for vehicle transportation or to the capacity provided by the system, and our focus is on capacity disruptions. We note the following general incident classes that can degrade both the safety and efficiency of the system.

- Planned Closures
- Capacity Impacts
  - Recurrent congestion
  - Debris in roadway [unplanned]
  - Right-of-way encroachment [unplanned]
  - Collision [unplanned]
  - Breakdowns/stopped vehicles [unplanned]
- Demand Impacts
  - Event-related congestion
  - Remote incidents causing demand shifts [unplanned]

The primary concern, from a near-term traffic-management perspective, is the development of non-recurrent congestion that ultimately leads to system delays and negative impacts on safety, including the increased likelihood of secondary incidents. Overwhelmingly, such congestion arises from unplanned capacity impacts caused by lane-blockages due to collisions, debris in the roadway, or right-of-way encroachment. As such, we focus our review on identifying these events.

The importance of rapid incident detection and verification is well established. For instance, using direct measurement of freeway performance in the presence of incidents as logged by the Caltrans District 12 TMC, Rindt et al. (2010) show that the delays caused by an incident are exponentially related to the speed with which full capacity is restored—assuming demand is constant during the disruption. Furthermore, the likelihood of a secondary crash increases by roughly 2.8%

for each minute the primary incident continues to be a hazard (Owens et al., 2009). This makes quick identification of such events a core TMC priority.

These facts have long been recognized by traffic management agencies, who have established protocols for responding to incidents. California Department of Transportation (Caltrans) traffic incident management guidelines characterize incident management as shown in Figure 1 (Caltrans, 2014). Per the manual the typical incident management responsibilities include the following, with the responsibilities distributed across TMC staff, Freeway Service Patrols (FSP), Traffic Management Teams (TMT), and Maintenance.

- Monitor traffic operations (TMC).
- Perform incident detection and verification (TMC, FSP, TMT, Maintenance).
- Protect incident scene (TMT, Maintenance).
- Perform first responder duties (Maintenance).
- Clear minor incidents (Maintenance/FSP).
- Implement traffic control strategies and provide supporting resources (TMT, Maintenance).
- Disseminate traveler information (TMC/TMT).
- Assess and direct incident clearance activities (Maintenance).
- Mitigate small vehicle fluid spills (Maintenance).
- Develop alternate routes (TMC, TMT, Maintenance).
- Assess and perform emergency roadwork and infrastructure repair (Maintenance).
- Assume role of Incident Commander, if appropriate (Maintenance).
- Support unified command as necessary (TMT, Maintenance).

In addition to these specific functions, there are cross cutting issues that complicate management. For instance, coordination with other agencies must be considered because jurisdictional responsibilities mean that specific responses must be implemented by the agencies controlling the resources involved (CSUSB, 2009). More generally, the guidelines define six distinct phases for incident management:

- **Notification/Detection**: the process by which the TMC and other traffic management agencies are notified of a possible disruption;
- **Verification**: the confirmation that an incident has occurred from an official source and the identification of the impacts, which are necessary to address the disruption;
- **Dispatch**: determination of necessary actions to clear the incident and its impacts, and communication to the assets necessary to effect those actions;
- **Response**: implementation of the dispatched actions, including marshalling of necessary assets and transporting them to the site and working to re-establish capacity and minimize impacts to the traveling public;
- **Clearance**: process by which demand/capacity balance is restored to normal conditions, including the dissipation of any abnormal queuing due to the incident impacts
- **Normal Conditions**: complete resolution of incident impacts.

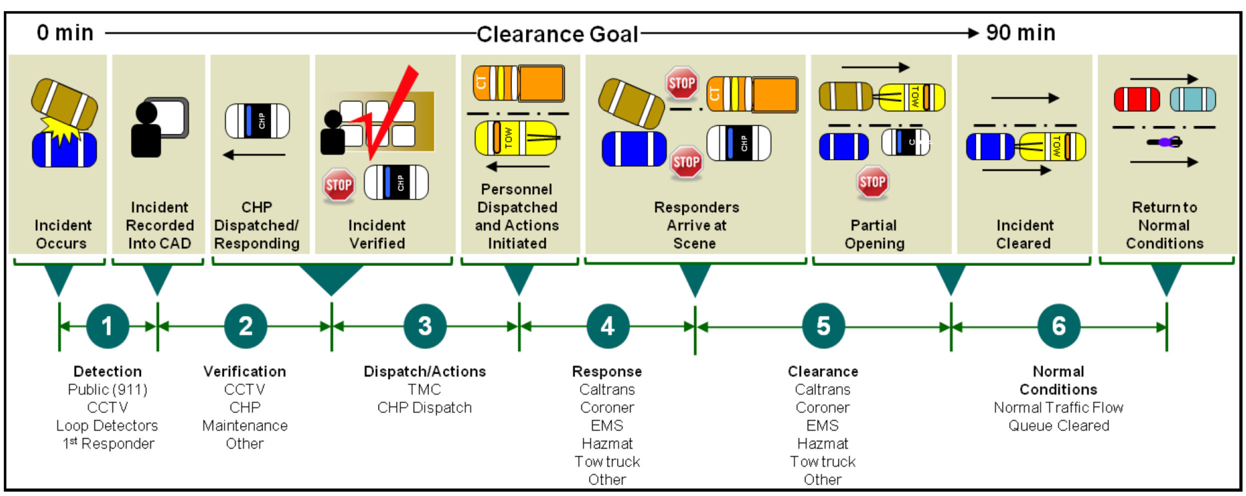

Figure 1 Incident Components (Caltrans, 2014)

Since incident response cannot begin until an incident is detected, the fundamental goal of enhanced situational awareness in the TMC is to speed the detection process such that response can begin earlier.

5 Conventional Incident Detection Methods

Incident detection has been a primary goal of traffic management for decades. Ozbay et al. (2005) offer a detailed assessment of incident detection methods circa 2005, which provides a useful starting point for this review. Here we break down the techniques into three categories: communication, patrols, and remote monitoring and consider the relative strengths and weaknesses of each.

Public communication methods for identifying incidents include roadside callboxes and cellphones, though the proliferation of cellphones since the early 2000s has diminished the role of roadside callboxes for incident reporting. In the present day, most publicly reported incidents will come via cellphone. These reports will typically filter from first-responders who receive initial notification of events such as accidents. The TMC typically will have tight collaboration with first responding agencies, such as the highway patrol and other emergency services, such that notifications to those agencies will be received nearly simultaneously in the TMC and which will initiate the verification, dispatch, and response actions. The benefits of these approaches are direct notification of the incident—usually by those affected. Such communications tend to occur rapidly after the event and therefore are effective for initiating TMC actions. However, less impactful disruptions, such as debris in the roadway, may or may not be reported via dedicated emergency channels. While these relatively minor disruptions do not involve collisions, they are precursors to secondary incidents that may involve loss of property or life. As such, they require supplemental techniques for quick identification.

Incidents are also reported via various official patrolling mechanisms. Police highway patrols have been a first-line reporting mechanism for decades as their surveillance of freeway operations for enforcement and safety often puts them in positions to be the first responder on the scene. FSP, TMT, and aircraft-based monitoring—often via media outlets—also have a role to play here as official sources of information. However, the cases in which such patrols are the first incident notification have diminished greatly with increase in cell-phone and other communications technologies. This is due to the fact that patrol-based notifications depend on the frequency and general coverage of patrols across large networks. It is more common that patrolling first responders are the first to provide *incident verification* to the TMC, which allows the development of a response plan. Thus, additional mechanisms are necessary to achieve wide-channel incident identification that includes the ability to detect “precursor incidents”

Toward this end, TMCs could benefit from automated methods for remotely monitoring and identifying incidents. The next two sections consider sensor-based Automated Incident Detection and AVID techniques respectively.

6 Automated Incident Detection

The development of algorithms to automatically detect disruptions to the transportation system has long been an application of interest for ITS. These systems have the primary goal of reducing the time to detection in order to initiate the clearance of a disruption as quickly as possible.

6.1 Performance Metrics

The performance of AID systems is generally characterized in terms of a number of primary metrics (Cheu et al., 2002):

- **Detection Rate (DR)** is the ratio of incidents correctly detected to the total number of incidents that occurred and is expressed as:

$$DR(\%) = \frac{\text{Number of incidents detected}}{\text{Total number of incidents}} \times 100 \tag{1}$$

- **False Alarm Rate (FAR)** is ratio of the number of times an algorithm identified an incident when none existed to the total number of cases the algorithm considered. It can be computed as:

$$FAR(\%) = \frac{\text{Number of false alarms}}{\text{Number of cases considered}} \times 100 \tag{2}$$

  Luk et al. (2010) point out that the more frequently an algorithm is applied (e.g., every 6 s vs every minute), the more potential there is for false alarms. As a result, care must be taken when comparing False Alarm Rate (FAR) across studies.

- **Mean Time-To-Detect (MTTD)** is the average time to detect an incident (t_i^{det}) from the time it occurred (t_i^{act}) and can expressed as follows:

$$TTD_i = t_i^{det} - t_i^{act} \tag{3}$$

$$MTTD = \frac{1}{n}\sum_{i=1}^{n} TTD_i \tag{4}$$

Wang et al. (2005) note that for effective use in TMC operations, an AID should have a short Mean Time-To-Detect (MTTD) while maximizing Detection Rate (DR) and minimizing False Alarm Rate (FAR). However, they point out that there is a correlation between MTTD and DR, as shown in Figure 2, whereby increasing MTTD typically increases DR and decreases FAR.

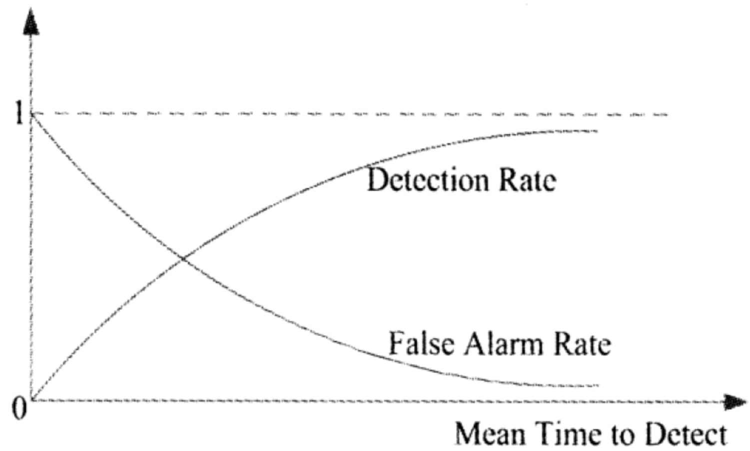

Figure 2 Relationship between MTTD, DR, and FAR (Wang et al., 2005)

Given these relationships, a given deployment must set the thresholds for each metric to obtain a balance that is appropriate for the application. One approach is to compute a performance index as suggested by Chung and Rosalion (1999)

$$PI = \left(\frac{100 - DR}{100}\right)^m \times FAR^n \times MTTD^p \tag{5}$$

Here, m, n, and p are used to represent the relative importance of DR, FAR, and MTTD respectively. A single performance index is useful as an objective function in optimizing calibration procedures for AID algorithms whereby a selected algorithm $\mathbf{A}$ is characterized by some set of parameters β and is evaluated against a training set to produce assessments of the performance measures (DR, FAR, MTTD)

$$\mathbf{A}(\beta) \longrightarrow (DR, FAR, MTTD) \tag{6}$$

These performance measures serve as inputs of the objective function, which we can then transform such that the decision variables of the optimization are the algorithm parameters β, so we can formulate a generic optimization

$$max\ PI = f(DR, FAR, MTTD) = f(\mathbf{A}(\beta)) \tag{7}$$

subject to any operational constrains on DR, FAR, or $MTTD$. The arbitrary AID algorithm $\mathbf{A}$ will generally be a non-linear function in the parameter space, so the optimization algorithm will likely require heuristic optimization methods specific to each AID.

The development of AID using ILD and other point-sensors has a long history and a number of notable reviews are available (Martin et al., 2001, Jacobson and Stribiak, 2003, Carson, 2010 and Pickford, 2015a).

6.2 AID Methodologies

Examples of AID in the literature extend back to at least as early as the 1974 development of the standard normal deviation (SND) algorithm Dudek et al. (1974). Other notable developments in AID include the "California Algorithm" (Payne et al., 1976) that employed decision trees comparing observed occupancy to historically-derived thresholds to identify incidents. The McMaster algorithm applied Catastrophe Theory to analyze the traffic state-space and identify incidents (Persaud et al., 1990). Lin and Daganzo (1997) proposed the "Berkeley Algorithm", which treats the time-series of occupancy as a random walk, with significant deviations flagged as potential incidents. Cheu and Ritchie (1995) and (Abdulhai and Ritchie, 1999a) (among others) developed AID algorithms using Artificial Neural Network (ANN) and Probabilistic Neural Network (PNN) approaches. Each of these solutions tended to advance the state of the art and performance but were highly dependent on incident detection thresholds. In practical application, thresholds that guaranteed low FAR (e.g., 2% or less) led to high MTTD (6-8 minutes) resulting in limited usefulness for practical deployment in which alternative communications channels outperform the systems (Mahmassani et al., 1999).

More recent efforts have sought to combine more advanced traffic state estimation with incident detection. Dabiri and Kulcsár (2015) use a macroscopic traffic framework to build a bi-parameter incident estimation that characterizes incidents with respect to nominal conditions. The spatio-temporal approach of Chung and Recker (2013) uses a simpler statistical method to characterize incidents as deviations from historical normal speeds. Wang et al. (2016) propose a particle filtering method to perform the joint estimation of state in incident detection with lower computational burden. Application to I-880 in California showed 100% detection with no false alarms. However, the time of detection relative to the actual onset of the incident was sensitive to model parameters, making calibration critical for implementation in practice.

In terms of practical deployment reviews, Luk et al. (2010) offer a useful assessment of AID in use in Australia using a range of standard algorithms. Their results are summarized in Table 1 and suggest quite high performance levels, particularly for ANN and PNN, which would imply high value for TMCs in deployment.

Motamed and Machemehl (2014) provide an evaluation of a dynamic time warping pattern classification method for incident detection (Hiri-o-tappa et al., 2010). In this approach standard deviation of observed speed over 1-min intervals is compared to characteristic precursors for previously observed incident conditions using a generalized distance metric. The distance metric is explicitly designed to minimize the impact of small distortions on the matching, which makes it more robust for pattern classification using noisy data. The method was applied to simulated data

Algorithm	DR (%)	FAR (%)	MTTD (min)
McMaster (Hall et al., 1993)	68-88	<0.01	2.1-3.2
DELOS (Chassiakos and Stephanedes, 1993a)	78	0.176	1.1
ANN (Ritchie and Cheu, 1993)	89	0	2.4
ANN (Ritchie and Cheu, 1993)	89	0	2.4
ANN (Dia and Rose, 1997)	83	0.065	3.4
PNN (Abdulhai and Ritchie, 1999b)	98-100	0-0.5	0.3-2.5
California 8 Algorithm (Chung and Rosalion, 1999)	71	0.005	8.9
DELOS (Chung and Rosalion, 1999)	73	0.03	5.5
ANN (Chung and Rosalion, 1999)	97	0.176	5.2
PNN (Zhang and Taylor, 2006)	93	0.057	2.7
ANN (Zhang and Taylor, 2006)	83	0.065	3.4
California 8 Luk et al. (2010)	84	0.075	8.3
ARRB VicRoads Luk et al. (2010)	84	FAR 0	6.7

Table 1 Summary of results from AID performance review in Australia (Luk et al., 2010)

and achieved a 100% DR with a MTTD of 125s. When applied to real-world data from a motorway in Pathumthani, Thailand, the system achieved 89% DR with a MTTD of 210s. FAR was not reported in either case.

Nathanail et al. (2017) recently proposed a traffic volume responsive method for AID. This technique performed on-line calibration of threshold values for the California #7 (Levin and Krause, 1979) and DELOS (Chassiakos and Stephanedes, 1993b) algorithms for different traffic volumes to make them more robust to changing traffic states. In application to the Attica Tollway in Athens, Greece, they report improvements to the existing algorithms with a 20% DR increase and 25% FAR decrease.

The rich literature in AID based upon conventional traffic sensors—particularly those that combine generalized state estimation with incident detection—suggests that these methods should be considered for continued development and deployment, especially in light of the continued development of big data analytics in traffic analysis. However, practical deployments in the United States have consistently demonstrated high false alarm rates to the point that very few TMCs employ AID due to high FAR (CTC & Associates LLC, 2012). As a result, AID systems likely require redundant systems to be useful for every day monitoring.

7 Automated Video Incident Detection

Using video technology to monitor traffic is a mature concept dating back well into the last century. Williams (2003) describes how "police forces (beginning with Durham in 1956) began to use CCTV to assist in the one-man operation of traffic lights (Norris et al., 2004)." As agencies gradually installed more CCTV and integrated them into TMCs, their use has become nearly pervasive (Kergaye et al., 2014). In this section, we review the core research in AVID before considering reviews of actual deployments to assess performance. We then provide a current survey of available commercial technologies that we identified and finish with a discussion of factors for successful AVID deployments.

7.1 Core Research and Technology

Coifman et al. (1998) offer a useful summary of the core elements of video image processing required for traffic analysis:

- **Automatic segmentation** of each vehicle from the background and from other vehicles so that all vehicles are detected.
- **Correctly detect all types of road vehicles**–motorcycles, passenger cars, buses, construction equipment, trucks, etc.
- **Function under a wide range of traffic conditions**–light traffic, congestion, varying speeds in different lanes.
- **Function under a wide variety of lighting conditions**–sunny, overcast, twilight, night, rainy.
- **Operate in real-time**.

They go on to summarize the primary approaches of early systems brought to market as either tripwire or vehicle tracking systems. Tripwire systems monitor detection zones for vehicles in a manner similar to loop detectors. Autoscope (Michalopoulos, 1991b) was one of the earliest examples of a tripwire system and used a threshold-based analysis of changes in specific pixels to determine the presense of vehicles. The system was later expanded to include AID capabilities and commercialized (Michalopoulos, 1991a). Descendents of this system are still a commercially active product. Other tripwire systems from the same era identified by Coifman et al. (1998) include

CCATS, TAS, IMPACTS and TraffiCam. Some early systems based upon vehicle tracking included CMS Mobilizer, Eliop EVA, PEEK VideoTrak, Nestor TrafficVision, and Sumitomo IDET.

The early generations of video processing struggled with a range of conditions including variable traffic conditions (congestion or high flow), occlusion, camera instability, lighting inconsistency including glare and shadows. Allieviating these shortcomings has been the focus of most of the research in the field since Coifman et al.'s (1998) review.

Gloyer et al. (1995) proposed an approach for recursively tracking freeway vehicles to identify prevailing speeds and use this for identifying congestion. To identify vehicles, their algorithm relies on identifying differences between a background image and the current scene. This object identification is coupled with a 3 dimensional model of the roadway scene and recursively processed to track vehicles as they move through the scene. The vehicle tracks are then converted into speeds. Experimental results used recorded images from freeways in Santa Ana, CA to evaluate performance, but only "promising performance efficiency" was reported without quantitative support. Further enhancements of this system do not appear in the literature.

Trivedi et al. (2000) addressed issues related to integrating multiple cameras as well as acoustic monitors into a single incident detection system, including novel (at the time) technologies such as omni-directional cameras that maximized coverage. They proposed a refined pixel-based segmentation approach that handled shadows more robustly than existing approaches at the time. Experimental results are limited in scope, but the authors do show the ability to distinguish between objects and their shadows. The multi-sensor scheme proposed for network wide coverage lays out some early concepts for network-wide sensor fusion that may be informative for today's Data Fusion (DF) problems.

Kastrinaki et al. (2003a) published a widely cited review of video processing for traffic applications that considered both roadway traffic monitoring and automated vehicle guidance. They consider the specific applications of automatic lane finding and object detection from the perspective of both fixed camera (roadway monitoring) and moving camera (autonomous vehicle) perspectives. They noted eleven distinct systems for traffic monitoring with static cameras as summarized in Table 2. Of these systems, we only found that Autoscope remains a viable commercial product.

Ozbay et al. (2005) performed detailed benefit/cost calculations for a variety of incident detection techniques. Their simulation-based results for CCTV deployments indicate a benefit/cost ratio ranging from 7.7 to 13.27. Fries et al. (2007) performed a similar simulation-based analysis of traffic cameras and computed a benefit/cost ratio of 12.0. The simulation approaches applied in both of these analyses limit their general applicability as the metrics are based upon specific modeled deployments with assumed rates of effectiveness.

System	Operating domain	Processing techniques
ACTIONS (Enkelmann, 1990)	Spatio-temporal	Optical flow field with spatial smoothness constraints
AUTOSCOPE (Michalopoulos, 1991b)	Spatial and temporal domain independently	Background frame differencing & interframe differencing, Edge detection with spatial and temporal gradients for object detection
CCATS (Hoose, 1991)	Temporal-domain with spatial constraints	Background removal and model of time signature for object detection
CRESTA (Postaire et al., 1987)	Temporal-domain differences with spatial constraints	Interframe differencing for object detection
IDSC (Takaba et al., 1984)	Spatial domain process with temporal background updating	Background frame differencing
MORIO (Dreschler and Nagel, 1982)	Spatial domain processing with temporal tracking of features	Optical flow field and 3D object modeling
TITAN (Blosseville et al., 1990)	Spatial operation with temporal tracking of features	Background frame differencing and Morphological processing for vehicle segmentation
TRIP II (Wan and Dickinson, 1990)	Spatial operation with neural nets	Spatial signature with neural nets for object detection
TULIP (Rourke and Bell, 1989)	Spatial operation	Thresholding for object detection
TRANSVISION (Wan et al., 1994)	Spatio-temporal domain	Lane region detection (activity map) and background frame differencing for object detection
VISATRAM (Zhu et al., 2000)	Spatio-temporal domain	Background frame differencing, Inverse perspective mapping, Spatial differentiation, Tracking on epipolar plane of the spatio-temporal cube

Table 2 Video-based traffic monitoring systems circa 2003 (Kastrinaki et al., 2003a)

Joshi et al. (2007) propose techniques for improving video tracking performance using support vector machines and co-training to improve handling of shadows in scenes. They also demonstrate some features of unsupervised machine learning that may be informative. We were unable to find any further extension of their research in the literature.

Fishbain et al. (2009) proposed a video-based traffic state estimator that is then applied to incident detection. In this system, flow, speed, and concentration are directly estimated from the video images and incidents are flagged based upon partitioning of the 3-D traffic state variable space using thresholds. The system does not appear to have been evaluated under real-world conditions, but offers an interesting model-based approach to incident detection that may be informative.

Loureiro et al. (2009) consider the problem of obtaining traffic information from uncontrolled, public video streams. This is an interesting question from a broader machine-learning perspective as the proliferation of public video streams provides a potentially rich source of traffic information. Though primarily a review, they identify the key challenges to using uncontrolled video for real-time traffic monitoring including:

- lack of control and knowledge of orientation (view angles, distance, etc) making it difficult to map onto a logical network
- view inconsistency caused by occlusion and other factors
- variable video quality
- environmental effects including weather and lighting issues (through this is not exclusive to uncontrolled video)

Though the authors do not offer a concrete path toward deployment, the proposal is worth revisiting in the coming years as machine learning and video processing technology continues to improve.

Chintalacheruvu and Muthukumar (2012) propose a video-based vehicle tracking system relying on a corner detection algorithm that requires less calibration than existing systems. Experimental results using video from the Las Vegas, NV area compare favorably to the existing commercial Autoscope installation based upon comparisons to ground truth measurements. The system was deployed in a queue warning system at work zones and on freeways during special events, though no evaluation of the system's performance for that application was provided.

Netten et al. (2013a) detail the findings of the Realising Advanced Incident Detection on European Roads (RAIDER) program, which was funded by a European consortium including TNO from the Netherlands, AIT from Austria, TRL from the UK, and FEHRL based in Belgium. In this review AVID systems are compared to three new types of AID systems anticipated by 2030. The first considered was eCall, whereby vehicles involved in accidents report automatically to emergency agencies—now a European mandate from 2018 forward. The second was nomadic devices whereby vehicles act as passive probes providing Floating Car Data (FCD) that is then used for AID. The third described cooperative systems in which vehicles actively detect incidents around them and report those detections centrally. Based upon an analysis of current technological capabilities and anticipated development, they conclude that "[v]ideo tracking and scanning radar systems are the only detection technologies considered in this project that can provide the required performance for accident and breakdown detection by 2020. These road side solutions should be considered as an intermediate solution till they can be replaced by [cooperative] in-vehicle or nomadic devices."

Li et al. (2014) offer a useful summary of video-based traffic monitoring. They note AUTOSCOPE, CCATS, TAS, IMPACTS and TraffiCam as tripwire or ILD-mimicing systems and contrast them to vehicle tracking systems typified by CMS Mobilizer, Eliop EVA, PEEK VideoTrak, Nestor TrafficVision, Autocolor, and Sumitomo IDET. They highlight that the latter systems struggle with vehicle occlusion, making camera placement critical.

Wan et al. (2014) describe a Real-time Highway Surveillance System using video analytics that includes stopped vehicle detection. Their system solves a number of deployment related issues, including automatic calibration. They compare it to an unnamed commercial product and claim superior traffic state estimation. However, the specific AVID evaluation was extremely limited as only one stopped vehicle event occured during the test, which was successfully detected.

Ren (2016) proposes a method for AVID that estimates traffic states (flow, speed, occupancy) in each lane by dividing them into monitored cells and tracking objects through the cells. Incident conditions are determined using a fuzzy state vector machine to classify traffic states corresponding to incidents. The results are compared favorably to the ILD-based California and McMaster algorithms for a limited set of test cases, with significant improvments in DR, FAR, and MTTD. However, the authors note their algorithm will suffer from the common AVID problems of environmental conditions and coverage.

Mehboob et al. (2016) propose a similar solution to Ren using customized video analytics to estimate speed and flow, which are then fed through a fuzzy logic analyzer that classifies these states into incident or non-incident conditions. Calibration of parameters appears to be done manually based upon *ad hoc* analysis of speed-flow data. Without a more robust calibration method, the results of this system are likely to vary significantly with the deployment.

Bottino et al. (2016) describe a video-based system that identifies traffic states using object detection and a flow analysis model. They claim the system can adaptively switch between learning and on-line modes based upon the stability of the flow model. The system has been used primarily for traffic state estimation, but the authors claim it has application for AVID.

7.2 Deployment Evaluations

There have been numerous evaluations of deployed commercial AVID systems over the past two decades. For instance, Ikeda et al. (1999) tested an AVID system produced by OMRON Corporation on the Metropolitan Expressway in Tokyo. The system used an imaging differencing algorithm to identify and track vehicles. Notable elements of the system included enhanced accuracy through the use of multiple cameras focused on the same scene and the ability to dynamically select baseline images to handle rapid changes in lighting. The system was integrated into the TMC using event-driven pop-up notifications. They report successful detection of 755 incidents (stopped/slow vehicles and debris in the roadway) with a FAR of 8.7%. OMRON doesn't appear to market any AVID systems today.

Martin et al. (2001) summarized the performance of a variety of AID approaches including ILD-based and AVID techniques as shown in Table 3. Though the applications are admitted to be difficult to directly compare due to methodological differences in the evaluations, the summary provides a useful reference point for reported AID performance at the time.

In a head-to-head test of commercially available AVID systems at the time, (Prevedouros et al., 2006) compared the performance of commercially installed Autoscope, Citilog, and Traficon systems in a freeway tunnel. The results were mixed, at best, with the authors citing reliability problems and wide-ranging false alarm and detection rates that were dependent on traffic state and, in particular, environmental conditions such as darkness, glare and other factors. They recommneded that the AVID systems evaluated needed further development and that their most useful application was for the detection of objects (i.e., debris) in lanes.

Margulici and Chiou (2007) performed a head to head test on the Citilog and Econolite AVID systems circa 2005. They found that Citilog and Econolite achieved incident detection rates of 86% and 81% respectively with false alarms rates of 14% and 19% respectively. They also found that the performance of the systems degraded significantly with weather and traffic conditions and suggested that careful camera placement could mitigate some of these factors.

Shehata et al. (2008) discuss environmental challenges for AVID. They specifically analyze two unnamed commercial systems deployed in two different cities for false alarms due to shadows,

Name	DR (%)	TTD (min)	FAR (%)	FAR basis	Installations	Projected SLC[a] Network false alarms per hour
APID	86	2.50	0.05%	Calc	Toronto, Boston	7.74
DES	92	0.70	1.87%	Calc	Toronto	289.48
ARIMA	100	0.40	1.50%	Calc	Laboratory	232.20
Bayesian	100	3.90	0%	n/a	Laboratory	0.00
California	82	0.85	1.73%	Calc	California, Chicago, Texas	267.80
Low-Pass Filter	80	4.00	0.30%	Calc	Laboratory	46.44
McMaster	68	2.20	0.0018%	Calc	Minnesota	0.28
Neural Networks	89	0.96	0.012%	Calc	Laboratory	1.86
SND	92	1.10	1.30%	Calc	Not Known	201.24
SSID	100	-	0.20%	Calc	Laboratory	30.96
TSC #7	67	2.91	0.134%	Calc	California, Chicago, Texas	20.74
TSC #8	68	3.04	0.177%	Calc	California, Chicago, Texas	27.40
Video Image Processing	90	0.37	3.00%	Tot	France	0.03
Cellular Telephones	100	-	5.00%	Tot	n/a	0.005

Table 3 Reported performance of AID algorithms circa 2001 (Martin et al., 2001). NOTE: (*a*) Projected false alarm rates for Salt Lake City network.

snow, rain, and glare. One city had a tunnel monitoring system with a FAR of 25%, of which 90% were due to static shadows in the scene. The second city had an installation of 6 cameras that were used for AID. The FAR of this system ranged from 48-80% depending on the camera. These false alarms were caused in roughly equal proportion by static shadows, snow/rain, glare, and other causes, though the specifics varied with the season. Noting the poor performance of these systems, the authors provide an in depth review of research and strategies for improving performance under various conditions. They recommend a number of approaches including incorporating atmospheric optics, employing multiple cameras, the use of hyper-spectral imaging, and the development of custom algorithms for each environmental condition.

In their review of AID methods employed in Australia, Luk et al. (2010) note that installed AVID systems had high false positive rates, particularly in tunnel installations:

Video equipment for monitoring and incident detection has been installed in most tunnels in Australia. The video incident detections are prone to high FAR because of environmental conditions (rain, wind and shadows) or reduced effectiveness because of visibility constraints (fog, night-time).

The authors go on to offer some specific recommendations for AID installations that generally apply to AVID, including "target values for calibration and operation of DR 80%, FAR 1% and MTTD 5 min."

Huang and Buckles (2012) evaluated the deployment of low cost cameras for traffic monitoring in Texas. Much of the focus of this effort was on designing the communications systems for wireless transmission of video signals. Significant discussion is given to the tradeoffs between video quality and communications bandwidth, which may be of use in the development of CCTV infrastructure in areas lacking sufficient communications infrastructure. Only limited AVID analysis was performed on detection of stopped vehicles using the commercial Abacus from Iteris and a custom TxDOT AVID system. During the test, only a single stopped vehicle event occurred, which was detected by Abacus system and no false alarms were noted in this test.

Simpson (2013) evaluated a number of commercial detection systems for wrong way vehicle detection on freeways in Arizona that included microwave, radar, and video (visual and thermal) systems. Though the specific vendors weren't specified, the results were sufficiently positive for them to recommend a combined approach using redundant systems to account for failed detections and false alarms.

Preisen and Deeter (2014) summarize the results of a pooled fund study of traffic VA for data collection and incident detection in Ontario, Canada as well as Iowa and Missouri. Systems evaluated included a thermal camera from DRS Technologies, Inc, the Abacus Video Analytics system from Iteris, Inc., an on-site Video Analytics system from Peek Traffic Corporation, the TrafficVision system for traffic data collection and incident detection, and the ENTERPRISE Next Generation Traffic Data and Incident Detection from VideoIQ. In addition to considering general VA applications, they define the Operational Concept for automated incident detection alerts in the TMC from VA. They specifically note the importance of camera coverage to capture the highest percentage of incidents possible while mitigating environmental effects on AVID performance. They make a qualified recommendation that VA is ready for practical application:

Video Analytics demonstrated that with proper location and configuration, detection of stopped vehicles and/or debris in roadway can have minimal false positives or 'false alarms' (as few as 0% false alarms), however the camera site is critical to achieve this. Slow traffic detections were found to have higher 'false alarm' rates. In addition, Video Analytics *demonstrated that it can be effective in supplementing existing mechanisms for incident detection (e.g. detecting/alerting operators of incidents they were not already aware of.)*

Ultimately, they conclude that commercial AVID technologies are viable as long as agencies and vendors agree to parameters defining acceptable performance and to on-going calibration and configuration that meet those standards.

Ishak et al. (2016) evaluated a number of commercial systems for performing traffic counts using existing video detection cameras installed at intersections in Baton Rouge, LA. The study performed manual counts at 20 intersections and compared them to counts determined by previously installed Econolite Autoscope systems using Multiple Logistic Regression and t-tests. Their findings showed that VA counts at 40% of the intersections showed statistically significant differences from the manual counts, which they attributed to poor calibration and maintenance. Thus, as with the pooled-fund study mentioned above, they recommended regular re-calibration of installed systems to maintain performance levels. Since these re-calibrations generally require vendor activities, they should be included in any service contract or budgeted for separately by the agency.

Bommes et al. (2016) offer a comprehensive review of video applications for ITS. In regard to AVID, they note Traficon (Versavel, 1999) and Autoscope (Michalopoulos, 1991a) as specific commercial products (without critical review) as well as the academic work of Shehata et al. (2008) and Fishbain et al. (2009). They conclude with the assessment that many traffic systems have a large number installed cameras that are not currently used for VA or AVID, which is a missed opportunity. They further suggest that temporary AVID installations in work zones would be particularly useful due to the greater potential for incidents.

Kim et al. (2017) offer a recent review of video analytics for traffic incident detection and vehicle counts. Much of their focus is on the factors that influence performance of video traffic analytics systems. Optimal placement varies with the specific technology and application, though camera heights of 30-60 feet were typical. Unsurprisingly, the quality of the video feed also was shown to have significant impact on the performance of the systems. Modern installations using high definition internet protocol (IP) cameras will likely provide suitable performance for modern commercial AVID systems, but the prevalence of legacy low-definition analog cameras in a particular deployment will be a factor in a system's ultimate performance. Numerous studies in their review also noted performance variation across lanes in traffic measurement applications. Based upon these findings, they performed a pilot study using an unnamed testbed involving 315 cameras and selected 21 for analysis using three different video quality settings. Incidents were identified for analysis using TMC logs to provide ground truth data. The system was capable of identifying incidents caused by wrong-way vehicles; stopped vehicles (using thresholds); congestion (using thresholds); slow speeds, and pedestrians. The results show the system's sensitivity to video quality, ranging from (DR=25%, FAR=30.9%) for lower quality video (bitrate <100 kbps) to (DR=80.4%, FAR=8.9%) for higher quality (bitrate >1000 kbps). The authors analyze the specific characteristics for both undetected incidents and false alarms. The false alarms were determined to be caused primarily by environmental conditions as well as by the camera being moved out of the preset position for which calibration was performed. They attributed the bulk of the undetected incidents to road markings (a cross-hatched gore point) confusing the algorithm.

A 2017 New South Wales government report on AID and and AVID made the following recommendations when considering AVID deployments:

> *Lighting is also an important consideration for use of AVID systems. In open air environments, AVID reliability for detection of incidents on sections with changing lighting conditions (ie areas that are regularly in shadow) may be limited. Operational measures may need to be taken to instruct the system not to detect incidents at those locations and prevent a high false alarm rate; however this will result in AID blind spots on the network. (NSW Government, 2017)*

7.3 Commercialized Technology Summary

The common capabilities of today's commercial VA and AVID systems are shown in Table 4 and include a broad range of capabilities. However, Wan et al. (2014) note that commercial offerings tend to be tailored to specific tasks rather than general purpose tools. This can be seen in the context of AVID in which specific products are designed to identify distinct incidents:

- Wrong-way driver (e.g., Traficon's VIP/D)
- Stopped vehicles (e.g., Econolite's Autoscope Solo Terra)
- Roadway debris (e.g., Iteris's Abacus).

As such, video processing systems come in a variety of forms including standalone integrated camera/analytics units, rack-mounted video processing hardware designed to process video streams provided by existing feeds and/or non-analytics units, and software solutions for accessing analytics and event data from existing video feeds. The most mature vendors offer products in all of these categories.

Traffic Data and Monitoring	
Speed	Speed of individual vehicles
Volume	The number of vehicles per time unit per lane
Occupancy	The average number of vehicles per lane
Traffic Flow	Total number of vehicles summed over all directions
Density	The density of vehicles per lane
Headway	Distance between vehicles
Gap time	Time distance between vehicles
Counts	Number of vehicles passing over a detection zone
Queue length	The length of the queue formed by waiting vehicles
Turn counts	The number of turns occurring at intersections
Automatic Event Detection	
Congestion	Congestion level
Stopped vehicles	Vehicles stopped on roadside
Slow/fast drivers	Speed not within nominal bounds
Wrong-way drivers	Wrong way
Pedestrians	Pedestrians on roadway
Debris	Trash or fallen objects
Fire/smoke	Fire or smoke in tunnel
Accident Recognition	Recognition of vehicle collision
System Technical Alarms	
Image Quality	Image quality is not sufficient for viewing or processing
Camera Movement	Camera's instability affects the quality of video output
Video Failure	No video output
PTZ out of home	PTZ camera is not focusing on right scene

Table 4 Typical features of commercial video analytics systems (Huang and Buckles, 2012)

We reviewed a range of video-based technologies available in the market based upon our research, including capabilities and the ability of these systems to potentially meet the AVID requirements. We performed a limited survey of **standalone cameras** for traffic monitoring as well as a number of **cameras with embedded analytics** based upon a review of the literature and known product lines. Because Caltrans District 12 made a commitment to camera hardware at the start of the project, this review was discontinued. Table 5 summarizes the standalone cameras identified during the review and Table 6 summarizes the cameras that incorporate embedded analytics.

Company	Product	Notes
Flir	ITS Series	
Peek Traffic	Color Video Detection Camera	
COHU	3960/3920	Analog
Pelco	ESPRIT/Spectra IV [SE(35X)/SL]	Analog
Vicon Industries	SVFT-PRS23	Analog
Elmo	ESD-380DR PTZ Camera	Analog
Iteris	Vantage RZ4	Analog
COHU	39803960/3960HD/3940	Network
Indigo Vision	9000 PTZ IP Dome Camera (36X)	Network
JVC	VN-V686WPBU	Network
Axis	Q6032-E / 233 / 232D+	Network
Bosch	AutoDome 300 Series	Network
American Dynamics	VideoEdge IP SpeedDome	Network
Panasonic	WV-NW964	Network
CP Technologies	FCS-4200	Network
Inscape Data	NVC3000	Network
CP Technologies	FCS-4100	Network
Sony	SNC-RZ50N	Network; requires housing
Vivotek	SD7313	Network
Axis	213 PTZ	Network; requires housing
ACTi	CAM-6610	Network
Canon	VB-C60/VB-C50iR	Network; requires housing
PiXORD	P-463	Network; requires housing, dome
PiXORD	P-465	Network
Advanced Technology	IPSD518S	Network; requires housing
Vivotek	SD7151	Network
Sony	SNC-RZ25N	Network; requires housing; web interface
Toshiba	IK-WB21A	Network; requires housing
CNB	ISS2765NW/ISS2765PW	Network

Table 5 Examples of commercial standalone cameras without analytics.

Company	Product	Notes
Flir (2017a)	ITS Series-AID	Thermal imaging camera with embedded AID for stopped vehicles, wrong-way drivers, pedestrians, debris in lanes
Flir (2017b)	ITS Series-Dual AID	Camera plus thermal imaging providing AID for stopped vehicles, wrong-way drivers, pedestrians, debris in lanes
Flir (2017c)	Traffibot HD	Embedded AID analytics as well as multi-stream encoding providing AID for stopped vehicles, wrong-way drivers, pedestrians, debris in lanes
Citilog (2017d)	XCam-Edge-AID	Embedded AID for stopped vehicles, congestion, pedestrian, wrong way and slow vehicles, and debris
Peek Traffic (2017c)	VideoTrak XCam	Supports AID for slow and stopped vehicles and can discriminate between fluid and congested traffic
Peek Traffic (2017b)	VideoTrak IQ	Limited to vehicle presence detection—primarily a replacement for intersection presence detectors.
Peek Traffic (2017a)	Unitrak	Coupled camera and video detector card designed for presence detection at intersections. Discontinued.

Table 6 Examples of standalone cameras with analytics.

The camera-based units noted above may be relevant to Caltrans districts that are looking to deploy new hardware in the field. However, for those that already have substantial investment in CCTV deployments, off-camera systems may be a more compelling choice. Table 7 summarizes the commercial rackmount video analytics systems we identified. These systems are standalone hardware-based units that are designed to analyze video streams from multiple video feeds obtained from independently installed cameras.

Company	Product	Notes
Iteris (2017)	VersiCam	Intersection and workzone detection (no AID)
Flir (2017d)	VIP-T/VIP-IP/VIP-HD	integrated automatic incident detection, data collection, recording of pre and post incident image sequences and streaming video in one board

Table 7 Rackmount analytics systems.

Finally, Table 8 summarizes software-based AVID solutions that are designed to operate on workstations or in cloud systems to provide VA and AVID analysis that can be integrated into existing

Advanced Transportation Management Systems (ATMS) installations. These systems are most consistent with the original goals of this project because the Caltrans District 12 TMC has a mature ATMS with existing hardware in place.

Company	Product	Notes
Citilog (2017b)	SmartTraffic-AID, SmartTraffic-i, SmartTraffic-ww	Software AID that can be installed on capable cameras to detect incidents and wrong way vehicles
Citilog (2017c)	VisioPaD+	Software AID that can run on Windows systems using existing hardware. Use existing PTZ cameras to perform AVID that can detected stopped vehicles.
Citilog (2017a)	MediaRoad	Software AID that can run on Windows systems using existing hardware. Incidents detected include: Stopped vehicle Congestion, Pedestrian, Wrong way, Slow vehicle
Kapsch (2017)	DYNAC	Full ATMS product includes CCTV AVID solutions as a component.
Trafficvision (2017)	TrafficVision	Software solution; provides data on lane occupancy rates, average rate of speed and incident detection of stopped vehicles, wrong-way vehicles, vehicle congestion, pedestrians in the road and slow speeds below a specified threshold for a specified duration
Telegra X-AID (2017)	X-AID	Reported Detection Rate: 95%; FAR: 0.72/day; Incidents detected: wrong-way Driving, Slow/Stopped Vehicle, Traffic Slowdown/Congestion, Pedestrians, Reduced or Loss of Visibility (smoke, fog, etc.), Debris on the Road, Dangerous Driver Behavior

Table 8 Software-based AVID.

7.4 Discussion and Synthesis

Our review of AVID technology identified a number of considerations for agencies considering deployments. The challenges associated with these systems include:

- **Tradeoffs between FAR, DR, and MTTD**: as noted Section 6 and in Figure 2, time to detection will generally increase with improving detection rate and decreasing false alarm rate. The balance between these performance measures must be defined by the agency, though it's worth emphasizing that a low FAR is particularly important for TMCs that are responsible for sizable networks as operator fatigue with high false alarm rates will invariably lead to AID systems being ignored.

- **Difficulty with particular environmental conditions**: numerous reviewed studies noted how lighting (darkness, glare, shadows, etc.) and weather (rain, snow) degraded AVID performance, even in modern systems[1]. To mitigate these problems, careful calibration for camera-specific environmental conditions is required.

- **High need for calibration and maintenance**: numerous reviews of practical deployments emphasized the need for ongoing calibration of AVID systems in order to achieve acceptable performance.

- **Coverage limitations**: the calibration requirements and performance of AVID systems makes obtaining full coverage of all managed roadways a challenging proposition. This can be mitigated somewhat through prioritizing placement of cameras, but gaps will inevitably remain.

Beyond the strict performance concerns are the range of costs associated with AVID systems. Up-front capital costs for camera hardware, communications infrastructure, and the AVID hardware/software solution can be substantial, though these costs are coming down as the technology matures. Of equal concern are the on-going costs, which include maintenance of the infrastructure and communications systems along with the on-going calibration of installed systems and any licensing fees associated with the chosen product.

The most fundamental takeaway is that no technologies available today are infallible for AID in general and for AVID in particular, so defining specific requirements up front is critical. The need

[1] This assessment was also offered during informal discussions with municipal agencies in Orange County operating video-based traffic signal detection systems.

for clear requirements is emphasized from the Pooled Fund study of Preisen and Deeter (2014) where they note:

- *A well scoped design, implementation, configuration, and testing phase allows the Video Analytics provider to configure and test selected cameras before realtime use;*
- *All parties agree to reach a 'go/no-go' decision on each camera after testing occurs and false alarms are found to be minimal; and*
- *There are provisions for periodic re-configuration of Video Analytics settings to ensure detections are appropriate (e.g. false positives are minimized).*

Netten et al. (2013b) provide an excellent guideline for formalizing such requirements and provide a sample for the AID use-case as shown in Table 9. Such qualitative assessments provide a means for specifying benefit bundles as a function of cost for particular use-cases. Candidate solutions can then be placed in a bundle category to simplify decision making.

Detection Rate (DR)	Low <= 50%	Medium > 50%	High > 80%	Very High > 99%
Detection Time (DT)	Very High >= 5 min	High < 5 min	Medium < 1 min	Low < 10 sec
Location Accuracy (LA)	Low >= 100 m	Medium < 100 m	High < 10 m	Very High < 1 m [1)]
False Alarm Rate (FAR) [False Alarms/day/km]	Very High >= 25	High < 25	Medium < 2.5	Low < 0.25
Suitability[2)]	Low (Does not satisfy all high priority requirements)	Medium (Satisfies all high priority minimum requirements)	High (Satisfies all *minimum* performance requirements)	Very High (Satisfies all performance requirements)
Costs	Very High €€€€	High €€€	Medium €€	Low €

Table 9 Qualitative assessment of incident detection performance and costs (from Netten et al., 2013b).
NOTES: (1) represents lane-level accuracy for incident detection;
(2) Suitability is defined in terms of each specified use-case

8 New Data Sources

Though traffic VA and AVID systems have largely matured in the marketplace, their shortcomings persist and will likely remain problematic in the long term—particularly issues related to coverage and environmental degradation in performance. It is therefore useful to consider alternative solutions that may supplement or supplant these systems.

8.1 Aerial Monitoring

Some recent consideration has been given to aerial monitoring of traffic networks in order to characterize traffic conditions and incidents. Aerial monitoring removes some of the restrictions of fixed-point monitoring by allowing sensors or cameras to by dynamically positioned depending on need. Latchman et al. (2005) described a proof of concept for the Florida DOT using Unmanned Aerial Vehicles (UAVs) to monitor traffic, but the practical test was canceled due to concerns from the Federal Aviation Administration.

More recently, Zhang et al. (2015) describe a routing model using UAV technology. They formulate an optimization problem for using UAVs to fill in coverage gaps for a fixed-sensor network. Through theoretical studies of real networks in Sioux Falls and Chicago, they demonstrate the feasibility of an optimal UAV routing algorithm to maximize observable network coverage over time and space subject to the operational constraints of the UAV. Results are not reported for conventional incident detection measures of DR, FAR, and MTTD.

8.2 Social Media and Crowdsourced Data

The explosion of ubiquitous computing is now so mainstream that mobile applications have sufficient penetration to provide levels of high-fidelity data that have previously only been seen in speculative simulation studies. Today, however, Information Service Providers (ISPs) such as Waze, which began a two-way data sharing program with Caltrans in 2016 (Caltrans, 2016), have deep user bases and are generating significant amounts of data regarding disruptions to the traffic supply. One analysis showed that on a typical weekday, Caltrans TMCs will monitor roughly 3,400 incidents whereas Waze users will report more than 64,000. This suggests great potential for what these new data sources can contribute with respect to system awareness for incident detection. However, it should be noted that the 3,400 incidents in the Caltrans system are vetted incidents that have been received and verified by TMC professionals. The Waze reports are crowd sourced data that have not been confirmed and likely contain many duplicates. In this sense, the Waze data serves as an additional channel for incident *notification*, but may contain a significant number of false alarms and inaccurate data ranging from location (Talasila et al., 2013) to incident specifics.

Gu et al. (2016) discuss using Twitter posts to identify incidents using natural language processing. In an application using 2014 data from Philadelphia and Pittsburgh, a small sample of Tweets were shown to match most of the incidents identified through official sources.

The range of new data with varying reliability made available by these new data sources imply a need for integrating these multiple disparate data sources with more conventionally trustworthy data via DF and analytics. A recent collection of articles Chowdhury et al. (2017) offers a good overview of the problem space and current approaches addressing these issues.

8.3 Connected Automated Vehicles for Incident Detection

Though the timelines vary from "it has already begun" to decades (USDOT, 2016), there is general agreement that CAV are the future of transportation and that these changes are potentially as transformative (if not more so) than the introduction of the mass produced car a century ago. The imminent disruption introduced by private sector advances will require forward thinking transportation professionals who can balance the traditional conservatism of transportation engineering with a willingness to embrace these new technologies and their implications.

Recognizing this coming change, the USDOT initiated development of the Connected Vehicle Reference Implementation Architecture (CVRIA) in parallel to the ongoing development of the NITSA and published the version 2.0 in 2015 (Sill, 2015) along with the USDOT's ITS Strategic Plan (Barbaresso et al., 2014), which laid out the plans to merge the NITSA and CVRIA into a single Architecture Reference for Cooperative and Intelligent Transportation (ARC-IT).

Even as fleets of CAVs increasingly take to the roadways in coming years, traffic management systems will continue to play a critical role in managing the infrastructure and rights-of-way that these vehicles will rely upon. Recognizing this, TMCs should be able to tap into CAV deployment to support TMC functions. Further, the advancements in machine learning generated by CAV development should be transferable to TMC technologies. The extent to which CAV systems to date already rely upon processing of video and various range-finding technologies suggests a number of directions that video-based machine learning from CCTV should benefit.

It is certain that OEMs will continue to develop vehicles with vision/sensor-based logic for collision avoidance (initially) and full autonomy (eventually). As this machine intelligence increases in sophistication, it's reasonable to assume that these systems will be characterizing particular classes of disruption (collision, debris, animal/pedestrians in the roadway, uneven road surface etc) in order to act on them properly. Once they can classify them it would be relatively simple to share these characterizations via connected technology to the TMC or other ISP. In a sense, this is just an incremental change from the use of social media for incident reporting. The only difference is that the vehicle Artificial Intelligence (AI) is assessing the scene and reporting it rather than a human driver. This is likely to result in more consistent characterization of disruptions and also simplify the handling of reports by the TMC since the reports will be more structured.

The impact of CAV on the development of AID has also been anticipated in the literature. In an early study related to mobile reporting, Skabardonis et al. (1998) analyzed Caltrans incident logs to study the impact of (manual) cell-phone reports on incident detection. Even in this relatively early era for cellphone market penetration, they found that cellular phones detected 38% of 264 lane-blocking incidents during the period with a FAR of 7%, with roughly 1/3 of the cell-phone reports capturing incidents not reported by the CHP.

More directly, Cheu et al. (2002) describe an early incident detection algorithm from FCD that compares directly measured section travel times to historical means via statistic testing to identify the likely onset of non-recurrent congestion. In a simulation-based evaluation, they note the relationship between the penetration rate and performance in terms of DR and FAR. They conclude that an instrumented vehicle penetration rate of 50% is necessary to achieve comparable performance to the best ANN system of the time (Ritchie and Cheu, 1993).

(Jerbi et al., 2007) describe a comprehensive "infrastructure-free" traffic information system whereby the collective of vehicles share information amongst each other using pervasive communications to develop a distributed database (Marca et al., 2006, propose a similar concept). Though the system doesn't explicitly identify incidents, it does provide decentralized guidance to all vehicles in the system based upon a shared knowledge base of traffic conditions. It is reasonable to extend this concept to identify incident conditions, with the TMC tapping into the collective database via roadside units or a cloud-based "blackboard" representing the collective knowledge of the system.

Abuelela et al. (2009) focused on identifying incidents based upon vehicle lane-changing behavior reported to roadside units and applying a Bayesian approach to identify incidents. In this research, they specifically focus on identifying incidents occurring under low-congestion conditions that ILD-based algorithms may struggle to identify. Based upon simulation modeling, they report that for moderate demand conditions of 900 vph/ln and 70% market penetration of reporting vehicles, the system can obtain 100% DR with 0% FAR with a MTTD around 3-minutes.

White et al. (2011) describe exactly such a system using smart-phone accelerometers to identify when a vehicle is involved in an incident and to provide automatic notification to first responders and by extension, the TMC. The authors note the existence of commericial systems providing similar capabilities, such as GM's OnStar, but argue that such systems are not pervasive and are expensive. Their smartphone based system taps into hardware that is common today to extend the capability to any car with an occupant carrying a mobile phone. This study is an interesting proof-of-concept, but does note how the lack of standards arising from bottom-up consumer-driven purchases complicates the problem of building an incident detection system from vehicle- or person-based technologies.

Khorashadi et al. (2011) describe a two-phase system that combines vehicle-based assessment of changing traffic conditions to identify incidents with a voting system facilitated by Vehicular Ad-hoc NETworks (VANET) to develop a consensus regarding incident likelihood. Simulation results show that with an equipped vehicle penetration rate of 25% the system achieves 100% DR with a 0.046% FAR, effectively outperforming all other loop-based AID as well as AVID systems as reported in an evaluation performed by Martin et al. (2001).

Bauza and Gozalvez (2013) describe a cooperative traffic detection system similar to Khorashadi et al. (2011). This system uses the equivalent of a Dedicated Short Range Communications (DSRC) Basic Safety Message (BSM) to report vehicle trajectories to roadside beacons. These data are used to estimate the traffic state in terms of speed and density, which are then converted to a prediction that an incident is occurring using fuzzy logic rules. If this occurs, the system polls nearby vehicles using multi-hop communications for their assessment of incident conditions to develop a consensus. Via simulation study, they report incident detection performance of severe incidents ranging from (64% DR, 45% FAR) to (90% DR, 13% FAR).

Smith (2015) describe a smartphone application that performs DF of incident reports from a variety of public and social media feeds to provide incident conditions to drivers. Testing of the system in four metropolitan areas in the United States showed FARs ranging from 21.5% to 8.7%. They do not report statistics for DR.

Baiocchi et al. (2015) describe an incident detection system using VANETs that transmit FCD to roadside beacons. These data are incorporated into a speed threshold-based incident detection algorithm whereby slow vehicles are essentially treated as voters indicating incident conditions. Using a simulation study of Rome, Italy, they report that with an equipped vehicle penetration rate of 50-75% they achieve a 98% DR with a MTTD of 47s (and a maximum of 2 minutes).

Salem et al. (2015) describe a system that uses Bluetooth sensors to estimate traffic conditions over time, using Markov chain analysis to produce course estimates of incident conditions. Field tests were promising, but too limited to generalize.

Asakura et al. (2015) propose two algorithms for incident detection using FCD combined with traffic models based upon bottleneck and shockwave analysis respectively. Simulation analysis showed some promise for the algorithms for low vehicle penetration rates, but more work is needed to lower MTTD.

Park and Haghani (2016) propose a Bayesian Neural Network (BNN) model to detect secondary incidents using road segment speed data obtained from cellular phones and other sources via the commercial INRIX system. Performance analysis shows FAR in the 10-20% range (though performance varies over time). Neither MTTD nor DR is specified. However, this system offers some unique structures tailored to the analysis of secondary incidents that may be of interest.

Similarly, Asakura et al. (2017) propose an AID that relies on FCD computed from Global Positioning System (GPS) trajectories and then applying two different algorithms to identify incidents. The first uses flow rate and travel time differences between adjacent sections to identify incidents. The second uses trajectories to estimate shockwaves that imply incident conditions. Using simulation analysis, they show that with a probe penetration rate of 10%, they were able to achieve a 58.1% DR with a FAR of 0.014% and a MTTD 11.3 minutes.

Khan et al. (2017) estimate traffic state using connected vehicle data (headways, stops, and speed) to estimate density and map this to Level-of-Service (LOS). This approach could identify incidents by identifying deviations from typical conditions, but no practical deployment has been performed.

Thomas and Vidal (2017) propose an incident detection system based upon passive traffic information from smartphone application data using a number of supervised learning classifiers that include Logistic Regression (Bishop, 2006) along with the two ensemble methods: a bagging classifier of logistic regression (Breiman, 1996) and an adaBoost classifier (Drucker, 1997). All of these algorithms were applied using a standard software library (scikit-learn, 2017). Simulation results using the idealized NetLogo Traffic 2 Lanes model (Wilensky and Payette, 1998) were mixed, with the DR in the 70-80% range and FAR in the 10-20% range.

Beyond these existing cases, there is clearly significant potential in combining the machine intelligence being integrated into modern vehicles with connected vehicle technology (either short-range or network communications) to decentralize detection and identify locations in the system in need of active monitoring by TMC personnel. Just as important is the notion that increasing intelligence embedded into the vehicles will produce detailed and continuous assessments of system performance. As demonstrated by the review above, the concept of vehicles as probes for collecting system data has been around since the advent of modern traffic management, but it is only in the very recent CAV advancements that the full capabilities of autonomous vehicles assessing their environment are becoming clear. We now can realistically anticipate vehicles reaching level-5 autonomy in which vehicle computers manage all aspects of the "dynamic driving task" in all conditions such that all humans are effectively passive passengers (see Figure 3). Based upon this, it is reasonable to assume that the developing intelligence of autonomous vehicles will include the ability to detect and identify a range of disruptions to the normal driving environment that are the common targets of AVID, such as disabled vehicles, debris in the roadway, pedestrian or other encroachment into the right-of-way, and so on. Add in the presence of pervasive connectivity that is anticipated to arrive even sooner—whether that is via DSRC, a 5G technology such as Cellular V2X, or some as-yet undeveloped system—it is highly likely that autonomous vehicles will actively identify and share high-fidelity assessments of disruptions to each other and to the system operators.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 3 Five levels of Autonomous Vehicles (SAE International, 2017)

Indeed, the aforementioned RAIDER program considered this issue specifically for improving incident detection in Europe (Netten et al., 2013a). This project identified a range of new technologies likely to become available for incident detection including new roadside technologies (such as Bluetooth detection and DSRC), nomadic devices (vehicles as probes), and cooperative systems in which CAVs identify incident conditions and report them to the managing agency. The new roadside technologies are likely to provide incremental benefits, but will not solve the common problems of infrastructure-based solutions to incident detection: high agency cost, coverage problems, low-fidelity data. On the other hand, the nomadic systems providing direct traffic stream data has near term potential for new incident detection algorithms. More significantly, cooperative systems, in which intelligence is embedded in the vehicle for incident detection that is then shared with agencies, have revolutionary potential for providing real-time system awareness to agencies. A decade ago, this type of system might have seemed unrealistic. However, the development of autonomous vehicle technologies is rapidly increasing vehicle intelligence. Since these vehicles must identify anomalies to navigate the complex traffic environment, their internal logic will necessarily be able to characterize various types of disruption. Burgeoning connected vehicle technology—whether roadside or network-based, will provide ready channels for sharing this information. Indeed, this type of sharing is already happening via social media and phone applications. The difference with the next generation of fully cooperative systems is that the intelligent assessment of incidents and hazards will come from in-vehicle systems rather than human assessment.

9 Integrating Incident Detection into the TMC

Given the rapidly evolving machine learning capabilities embodied by CAV and big data developments, TMC operators should focus their system improvements in a manner that couples the best characteristics of existing technology with new technologies that have the highest potential for benefit. There is clear value in infrastructure-based CCTV as a tool for remote assessment of traffic conditions from the TMC. However, the cost/benefit of AVID should consider how these other technologies may provide similar assessments that perform better in all environmental conditions and provide complete coverage of the network.

Furthermore, it is clear that the TMC's role will change with increasing penetration of CAVs and their supporting technology. Fundamental questions remain unanswered:

- How can the TMC access the data streams being generated by individuals and their service providers to obtain better information about the system?
- How can the TMC *use* and manage the extreme amounts of data arising from CAV and the intelligent Internet of Things (IoT) infrastructure?
- Are CAV part of the control system, assets to manage indirectly as they have been conventionally, or some combination of the two?

One thing we can say is that the specific technologies that will dominate the transportation system in the coming decades cannot be known with certainty. Managers of the system will be best served by understanding the *functional* capabilities of potential technologies and building systems to integrate those capabilities should they become a reality. This flexibility is especially valuable in a time of technological transition when organic coordination maximizes adaptability to change (Utterback, 1994). The ARC-IT (Iteris, Inc., 2017) is providing this functional structure and includes TMC incident detection as a core functional object. It therefore serves as a good starting point for answering these questions. However, it does not explicitly consider how new technologies from the Internet of Things (IoT) and CAV landscape can service those functions, probably due to their relative immaturity for traffic applications. Thus, the question remains of what is the best way to leverage these capabilities and incorporate them into operations.

El Faouzi et al. (2011) provide a highly cited review of integrating ITS data streams into TMC operations that focuses on data fusion techniques. They break down the prevailing fundamental multi-sensor DF methods into statistical (multivariate analysis and data mining), probabilistic (Bayesian and other probabilistic techniques), and AI approaches (ANN, evolutionary algorithms, etc). However, they point out that data fusion in complex systems, such as traffic networks, requires a layered approach—specifically noting the contributions of the defense industry in the area. They describe five levels of fusion for transportation that characterize the development of complete situational awareness of the managed system:

1. **Level 0:** pre-processing data from each source to common formats and representations;
2. **Level 1:** gathering data from all sources into a common framework for analysis;
3. **Level 2:** state estimation using Level 1 data sets and other institutional knowledge;
4. **Level 3:** incident/event identification and processing in the context of state estimation; and
5. **Level 4:** continual refinement and integration of new information

Modern TMCs generally perform some version of each of these levels of fusion. However, the traditionally siloed nature of traffic data analysis systems adds to the challenge of integrating disparate data sources into a global picture. Improvements to Level 0 and Level 1 processing to emphasize consistency in how data represent the system is critical. Here, standards such as the ARC-IT are critical for guiding this process such that heterogeneous products can be combined into a functioning whole.

Level 2 state estimation is still in its adolescence—particularly in the TMC. Augmenting data from traditional point sensors with new sensors including VA systems, FCD, social media and other public sources, and cooperative CAV systems will surely lead to advances. Furthermore, as the extensive review in this report shows, the Level 3 goal of incident identification is feasible using a variety of technologies with the ultimate solution likely to require leveraging the strengths of a combination of technologies in order to meet the operational goals of the TMC.

The as-yet-unsolved challenge is how to effectively achieve these goals incrementally. Undoubtedly, success will require systems engineering by creative professionals who can envision the possibilities of new data sources. This need is echoed in Kergaye et al.'s (2014) review of TMC operations across the country in which they note the importance of hiring a systems engineer "to ensure compatibility between ITS components and overall systems architecture."

10 Conclusion

This report has provided a broad review of technologies for improving the TMC's situational awareness of the transportation system with a particular focus on incident detection in general and AVID in particular. We have considered the general characteristics of incident management and noted the fundamental importance of quick incident detection to support rapid mitigation of disruptions in order to maintain the efficiency and safety of the system. Detailed reviews of a range of conventional and automated detection methods, including a number of field evaluations show that AID is an achievable goal. However, there is no single solution that can provide globally satisfactory performance on its own. As such, TMCs should continue to explore the possibilities of new data streams that will become available with the transformation of the vehicle fleet with connected and automated vehicle technologies.

We offer the following recommendations for the development of situational awareness capabilities in the TMC that can effectively identify incidents in order to initiate effective responses.

- **Sensor-based AID technologies have been repeatedly shown to be effective in theory** but widespread practical deployments are limited. It is possible that in live management settings, sensor-based AID algorithms do not provide a sufficient upgrade over manual monitoring of sensor data and incident notifications received through other channels, making the benefit/cost unattractive to TMCs.

- **AVID technologies can perform well under specific conditions** though environmental performance degradation and coverage issues mean that deployments should be selected carefully to maximize effectiveness. In many cases, TMCs already have CCTV installations, so AVID systems can enhance the value of existing capital expenditures. The systems also have the advantage of offering a mechanism for rapid incident verification through manual control of the camera once an automated alert is received.

- **Specification of system performance expectations is critical**. This specification should be specifically aware of how additional information can be incorporated effectively into existing TMC processes in order to justify the deployment as well as provide mechanisms for post analysis to provide ongoing calibration and refinement.

- **Calibration and refinement are critical to success**. Multiple evaluations reviewed emphasized the need for on-front and ongoing calibration and refinement in order to maintain system performance. Changes to the transportation infrastructure, seasonal variations, and other dynamic changes can all degrade installed systems over time. Systems that use machine learning and self-calibration techniques should be prioritized as these will minimize ongoing maintenance costs.

- **TMCs should make Data Fusion and multi-technique machine learning the fountainhead of TMC intelligence**. The performance of individual incident detection technologies, whether based upon traditional point sensors, FCD, AVID, or CAV show a range of strengths and weaknesses with respect to the tradeoffs between DR, FAR, and MTTD. Thus, TMCs would be best served by employing multiple methods and merging them into a broader situational awareness via DF algorithms that combine the best characteristics of learning algorithms with local knowledge to maximize applicability to real-time management.

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