Smoothing Algorithms for Incident Detection

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The majority of automatic incident detection algorithms aim to identify traffic incident patterns but do not adequately investigate possible similarities in patterns observed under incident-free conditions. A classification of major traffic disturbances on freeways is presented. On the basis of this classification, an incident detection logic is developed with the traffic features that result in the best distinction between an incident and other disturbances. The new logic, DELOS (Detection Logic with Smoothing), employs smoothed detector occupancy measurements to signal an incident when significant temporal changes of the smoothed occupancy occur. Three types of smoothers-average, statistical median, and exponential-are considered, leading to corresponding algorithms. The structure of the proposed algorithms is presented and compared with previous algorithms. Comparative evaluation of test results with rush-hour traffic and incident data from I-35W in Minneapolis reveal the improved performance of the proposed method.

Freeway incident detection has traditionally been formulated as a two-hypothesis problem, incident versus nonincident traffic (1-3) or incident versus recurrent congestion (4). Few researchers have attempted to distinguish incidents from other traffic phenomena that may have a noticeable effect on traffic [e.g., traffic pulses (5) and compression waves (6)]; further, no single study has considered all major disturbances. These disturbances include random traffic fluctuations that appear frequently and account for a significant portion of false incident alarms.

An incident detection scheme is developed that features simple-occupancy tests and aims to distinguish incidents from other disturbances. The detection scheme is part of IDENTIFY (Incident Detection Enhancements for Traffic In Freeways), a project evolving in two major directions, one employing filtering and a second focusing on neural network applications.

First presented in another article by the authors (7), the proposed logic, DELOS (Detection Logic with Smoothing), uses filters that smooth the raw data over sufficiently large time windows to eliminate short-duration traffic disturbances, such as random fluctuations, traffic pulses, and compression waves. Further, it employs comparisons of the smoothed occupancy over time to distinguish between slowly emerging recurrent congestion at bottlenecks and fast-evolving incidents.

The objectives of this work are to (a) introduce a multievent detection formulation and assess the capabilities of the original algorithm in the multi-event traffic environment and (b) perform sensitivity analysis with several filters that are widely used for smoothing time series data. For smoothing detector occupancy measurements, three types of smoothers are considered—moving average, statistical median, and exponential.

The resulting algorithms have been tested with data from I-35W in Minneapolis and compared with previous algorithms tested with the same data. The wide diversity of the test site in terms of geometric configuration, detector spacing, and location with respect to ramps and the diversity of the incident set with regard to incident type, severity, and location reveals the capability of the proposed detection structure to perform in a wide range of conditions. However, algorithm development and testing have been confined to rush-hour operations.

Test results indicate that, during the peak period, at approximately 60 percent detection rate, DELOS algorithms produce one false alarm per hour in the 8.8-km (5.5-mi) test section, which includes 14 detector stations. This represents a significant false alarm rate reduction in comparison with several previous algorithms.

BACKGROUND

Despite substantial research, algorithm implementation has been hampered by limited performance reliability, substantial implementation needs, and strong data requirements. To investigate the application issue, the authors conducted a survey of transportation departments in the United States and Canada on incident detection strategies currently used in traffic management systems (8,9). The survey results indicate that several departments have implemented an incident detection plan. Traffic information is typically collected from loop detectors and includes occupancy and volume averaged at 20 to 60 sec intervals, usually across all lanes. Detector spacing along the freeway is .5 mi on average. Certain systems (e.g., Ontario's Queen Elizabeth Way) also use paired detectors to collect speed data. In a demonstration project in Connecticut, overhead mounted radar detectors will return speed and volume data for incident detection. In Virginia, a switch from loop to video detectors is under way.

Most systems use a California algorithm (6) for incident detection. The original California algorithm is used in Minnesota, Ontario, and Virginia. The modified California Algorithm 2, which additionally requires persistence of the incident alarm for two consecutive periods, is used in Los Angeles

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and Seattle. Algorithm 7 is used in tunnel locations in Seattle. Different algorithms are often used, depending on traffic conditions.

In other cities, locally developed algorithms have been implemented. In Connecticut, a simple algorithm indicates an incident when speed drops below a threshold. In Illinois, a Bayesian approach (10) used the relative spatial occupancy difference as detection parameter. The approach focused on using the probability distributions of the detection parameter under incident and incident-free conditions for determining an optimal detection threshold. Because of its excessive computer time requirements, the Bayesian algorithm was replaced by a simpler one that considers the occupancy difference between the upstream and downstream station; an incident is signaled if this difference continuously exceeds a threshold for 5 min. Although the 5-min persistence test results in long response times, this is preferable to responding to frequent false alarms.

Thresholds for operational algorithms have been typically calibrated by trial and error (in Los Angeles and Seattle), empirical experimentation on historical data (in Illinois), and performance curves obtained from multiple runs of the respective algorithm on the data with incrementally changing thresholds (in Ontario). In Los Angeles, algorithms are frequently recalibrated, especially at locations that produce frequent incident alarms. Algorithm output consists of either textual description (as in Illinois, Virginia, and Seattle) or color computer graphic maps (as in Los Angeles, Minnesota, and Ontario). In the latter case, several congestion levels are indicated with different colors, and incidents are separately indicated (e.g., with flashing red).

Most systems have not quantitatively assessed the operational performance of algorithms in terms of detection and false alarm rates. In Ontario, off-line evaluation of the California algorithm produced a large number of false alarms. Ontario is consequently switching to a promising Canadian algorithm (4); this algorithm, in an off-line evaluation, achieved false alarm rates of 1 per station every 64 hr at 75 percent detection. However, In Illinois, where it was also evaluated off-line as a potential substitute of current methods, it resulted in good detection after a difficult calibration period, but the false alarm rate was not satisfactory.

To date, high false alarm rates have prevented implementation of fully automated incident detection. Instead, algorithm alarms typically trigger the operator's attention; the operator verifies the validity of the alarm and decides on the appropriate incident response. In certain cases, operators assume that frequent alarms are false, and they tend to ignore them (as in Illinois). In Los Angeles, incident response is initiated only after an incident has been reported by motorists or a highway patrol officer. Elsewhere, incidents are identified via closed-circuit television cameras (Minnesota) or review of the raw data by the operator (Illinois). Incident detection, especially in the latter case, heavily relies on the expertise of the operator.

Detector failure is an additional concern. Although malfunctioning detector rates have not been systematically assessed (in Los Angeles four to five malfunctioning detectors are identified and repaired weekly), they lead to significantly deteriorated algorithm performance. In certain systems (e.g., Seattle) specific types of detector failure are preempted by measurement validity checks.

TRAFFIC DISTURBANCE PATTERN CLASSIFICATION

Effective incident detection requires consideration of all major sources of false alarms. In particular, traffic flow presents a number of inhomogeneities that are difficult to distinguish from those driven by incidents. Events producing traffic disturbances include incidents, bottlenecks, traffic pulses, compression waves, and random traffic fluctuations. Sensor failure, also treated as an event, is only related to the measurement component of detection systems. The major characteristics of each event are discussed in the following sections.

Incidents

Incidents are unexpected events that block part of the roadway and reduce capacity. Incidents create two traffic regimes, congested flow upstream (high occupancies) and uncongested downstream (low occupancies), as indicated in Figure 1 for a typical accident blocking moving lanes. Two shock waves are generated and propagate upstream and downstream, each accompanying its respective regime. The congested-region boundary propagates upstream at approximately 16 km/hr (10 mph), and its value depends on incident characteristics, freeway geometry, and traffic level. Downstream of the incident, the cleared region boundary propagates downstream at a speed that may reach 80 km/hr (50 mph) (6).

The evolution and propagation of each event is governed by several factors, the most important of which are incident type, number of lanes closed, traffic conditions before incident, and incident location relative to entrance or exit ramps, lane drops or additions, sharp turns, grade, and sensor stations. Other, less important factors, which are harder to model, include pavement condition, traffic composition, and driver characteristics.

Incident patterns vary depending on the nature of the incident and prevailing traffic conditions (6). The most distinctive pattern occurs when the reduced capacity from incident blockage falls below oncoming traffic volume so that a queue develops upstream. This pattern, which is clearest when traffic is flowing freely before the incident, is typical when one or more moving lanes are blocked following severe accidents (Figure 1). The second pattern type occurs when the prevailing traffic condition is freely moving but the impact of the incident is not severe. This may result, for example, from lane blockage that still yields reduced capacity higher than the volume of incoming traffic. This situation may lead to missed detection, especially if the incident is not located near a detector. The third type characterizes incidents that do not create considerable flow discontinuity, as when a car stalls on the shoulder. These incidents usually do not create observable traffic shock waves and have limited or no noticeable impact on traffic operations. The fourth type of incident occurs in heavy traffic when a freeway segment is already congested. The incident generally leads to clearance downstream but a



FIGURE 1 Incident pattern (I-35W North, 11/21/89).

distinguishable traffic pattern develops only after several minutes, except in a severe blockage. This type of incident is often observed in secondary accidents at the congested region upstream of an incident in progress. freeway segment involving a lane drop between the first two and a lane addition between the second and third stations. Under normal conditions, the three stations operate at different average occupancy levels. This difference is more pronounced between stations 61S and 62S.

Bottlenecks

Bottlenecks are formed where the freeway cross-section changes (e.g., in lane drop or addition). While incidents have only temporary effects on occupancies, bottlenecks generally result in longer lasting spatial density or occupancy discrepancies. A typical bottleneck is shown in Figure 2. The figure presents occupancy measurements at three consecutive stations of a

Traffic Pulses

Traffic pulses are created by platoons of cars moving downstream. Such disturbances may be caused by a large entranceramp volume caused by the exodus from a sporting event, for example. The observed pattern is an increase in occupancy in the upstream station followed by a similar increase in the



FIGURE 2 Occupancy measurements at bottleneck.

downstream station. Because of ramp metering during the testing period, traffic pulses are rarely observed in this data set.

Compression Waves

Compression waves occur in heavy, congested traffic, usually following a small disturbance and are associated with severe slow-down, speed-up vehicle speed cycles. Waves are typically manifested by a sudden, large increase in occupancy that propagates through the traffic stream in a direction counter to traffic flow (Figure 3). The data reveal that compression waves result in significantly high station occupancies of the same magnitude as those of incident patterns.

Random Traffic Fluctuations

Random traffic fluctuations are often observed in the traffic stream as short-duration peaks of traffic occupancy. These fluctuations, although usually not high in magnitude, may form an incident pattern or obscure real incident patterns.

Detection System Failures

Detection system failures may be observed in several forms, but a particular form has resulted in a specific pattern in the data observations discussed here. This pattern is observed with isolated high-magnitude impulses in the 30-sec volume/ occupancy measurements, appearing simultaneously in several stations. These values are considered outliers or impulsive data noise.

PROPOSED ALGORITHM DESCRIPTION

The authors' review of incident detection strategies that are currently used indicates that algorithms that are intuitively appealing, computationally simple, and based on widely available aggregate (20 to 60 sec) traffic data are most likely to be implemented in freeway control systems. Within this specification, the proposed logic aims to develop simple occupancy tests to distinguish incidents from other traffic disturbances. Two major characteristics can be used for this purpose. First, incidents result in rapid temporal changes in traffic conditions. Second, incident duration is longer than that of other disturbances.

The first characteristic distinguishes incident congestion from bottleneck (recurrent) congestion, which evolves more slowly. This is because recurrent congestion results from demand increasing over capacity at bottleneck locations. The demand increase generally does not occur as fast at incident locations. The duration characteristic can differentiate incidents from short-duration disturbances. The basic concepts behind the algorithm development (7) are summarized next. The major focus of the current effort is to investigate the capabilities of the method to avoid signaling false alarms across each type of traffic disturbance and to perform sensitivity analysis across different types of smoothing filters.

DELOS algorithms involve smoothing occupancy measurements to distinguish short-duration traffic inhomogeneities from incidents. When an inhomogeneity is present, smoothing eliminates or diminishes its impact; on the other hand, smoothing does not substantially modify the incident pattern if its duration is greater than the number of terms in the smoother. Although smoothing may conceal the patterns of some nonsevere incidents, the large reduction in false alarms compensates for a few possibly missed incidents. Test results indicate a significant reduction in false alarms as compared with similar algorithms [e.g., Standard Deviation (1), Double



FIGURE 3 Compression wave (I-35W South, 11/16/89).

Exponential (2), and California (6)], which attempt raw data manipulations.

Further, in a manner similar to but more effective than previous algorithms, the proposed structure attempts to distinguish recurrent from incident congestion on the basis of slow or fast evolution of congestion, respectively. In particular, the distinguishing logic is based on temporal comparison of the detection variable, spatial occupancy difference between adjacent stations. For comparison, the incident test of the California algorithm considers occupancy reduction at the downstream station; however, such reduction is not always observed during incidents.

Two smoothed values are considered for the detection variable: one represents current traffic conditions, and the other represents past conditions. For an incident occurring at time t, define $OCC_i(t + k)$, smoothed occupancy at station i from k occupancy values after t, and $OCC_i(t)$, smoothed occupancy at station i from n occupancy values before t, where k and n represent the window size to smooth the data for the current and past periods, respectively. The incident is likely to create congestion in upstream station i and reduce flow in downstream station i + 1, leading to a high value of spatial occupancy difference, $\Delta OCC(t + k)$, as described in Equation 1.

$$\Delta OCC(t + k) = OCC_{i}(t + k) - OCC_{i+1}(t + k)$$
(1)

Further, to distinguish from bottleneck congestion, the spatial occupancy difference $\Delta OCC(t + k)$ for the current period is compared with the corresponding value $\Delta OCC(t)$ from the past period (see Equation 2).

$$\Delta OCC(t) = OCC_i(t) - OCC_{i+1}(t)$$
(2)

Both tests, congestion and incident, are normalized by the highest value of the two occupancies, upstream and down-stream, as defined in Equation 3.

$$maxOCC(t) = max[OCC_{i}(t), OCC_{i+1}(t)]$$
(3)

This reflects changes with respect to existing conditions before an incident. The normalization increases the potential for algorithm transferability across locations. In summary, the proposed detection logic involves two tests, congestion (Equation 4) and incident (Equation 5), where T_c and T_t are the respective thresholds.

$$\frac{\Delta OCC(t+k)}{maxOCC(t)} \ge T_c \tag{4}$$

$$\frac{\Delta OCC(t+k) - \Delta OCC(t)}{maxOCC(t)} \ge T_I$$
(5)

The major concerns in selecting a smoothing technique are related to its effectiveness in eliminating undesirable sources of false alarms, the extent to which smoothing distorts the information content of incident patterns, and the detection delay imposed from the need to obtain a number of measurements while an incident is in progress.

Moving average, a linear transformation, is a simple but effective smoothing technique. The occupancy measurement at time t and detector station i, $o_i(t)$, is smoothed via Equation 6.

$$OCC_{i}(t) = \frac{1}{L} \sum_{i=0}^{L-1} o_{i}(t-l)$$
(6)

Moving averages of a different order, L = k and L = n, corresponding to smoothing factors 1/k and 1/n, are used for the current and past periods, respectively. Window sizes kand n are selected to optimize algorithm performance. An additional length constraint is imposed on k because long smoothing windows (e.g., longer than 10 samples) would result in excessive delays in algorithm response. This linear transformation, although effective in removing traffic fluctuations, distorts information-bearing edges (i.e., step-like changes caused by incidents), possibly obscuring their information content. An alternative, nonlinear, transformation employing the statistical median of the data window (see Equation 7) has been considered to address the issue.

$$OCC_{i}(t) = median [o_{i}(t), o_{i}(t-1), \dots, o_{i}(t-L)]$$
 (7)

Exponential smoothing is a third smoothing technique, extensively used in determining data trends. The general form of the smoother is shown in Equation 8, where α is the smoothing factor.

$$OCC_i(t) = \alpha \cdot o_i(t) + (1 - \alpha) \cdot OCC_i(t - 1)$$
(8)

A number of algorithms have been developed along the three major types of smoothing. The algorithms are coded as DELOS x.y (z,w), where x and y represent the smoother type used for the past and current periods, respectively, with the values of 1 for average, 2 for median, and 3 for exponential smoother. Further, z and w represent the past and current period window sizes to smooth the data in the average or median smoother. In exponential smoothers, z represents the smoothing factor, and w is the time lag k between the end of the past and the end of the current period. In combinations of exponential smoothing for the past data with other types of smoothing for the current, the window size for the current data period represents the above time lag. For example, DELOS 3.1 (0.05, 6) smooths past data exponentially with $\alpha = 0.05$ and current data with an average 6-sample window.

DATA DESCRIPTION

The proposed algorithms and several algorithms from the literature were tested with actual data. In particular, 140 hr of afternoon peak-period (4:00-6:00 p.m.) traffic data from a 8.8-km (5.5-mi.) segment of southbound I-35W in Minneapolis (Figure 4) were collected through the Minnesota Department of Transportation Traffic Management Center. The freeway segment has 3 lanes along most of its length. It includes 2 major bottlenecks. The first is in the merging area between I-35W southbound and Highway 62 westbound, where 3-lane I-35W drops a lane for a short section. The typical occupancy pattern in these 3 stations is presented in Figure 2. The second bottleneck location is at Minnehaha Creek bridge, north of Diamond Lake Road, where a freeway segment with an uphill grade is followed by elimination of the shoulder at the bridge. The test segment includes four entrance and five exit ramps.



FIGURE 4 Study site in Minneapolis (I-35W).

The traffic data consist of 30-sec volume and occupancy measurements from loop detectors, forming 14 stations imbedded along the road, 0.5 to 1.1 km (0.3 to 0.7 mi) apart. The 30-sec data are averaged across lanes, producing one measurement for each station at every time interval. This traffic data set is a typical one, collected routinely in most U.S. cities. Algorithm development has been aligned with typical longitudinal data availability and, therefore, the algorithm can be implemented across a wide range of systems, including those that do not place detectors in all lanes. Algorithms that depend on additional information (e.g., measurements for each lane, speed, and shorter time measurements), although potentially effective, cannot be implemented across all systems.

During the testing period, 27 incidents were reported by the traffic operator. Detection was accomplished mostly through closed-circuit television cameras along the freeway segment. Of all incidents, 15 were accidents, 3 occurred in the moving lanes, and 12 were moved to the shoulder. According to the operator log, 6 accidents had severe impact on traffic operations, 4 happened in an already congested region, 3 had limited congestion impact on traffic, and the rest were not classified. Besides the accidents, 12 vehicle stalls were observed. All occurred on the shoulder, 1 had a severe impact on traffic, 1 occurred in an already congested region, 7 produced limited congestion, and 3 were not classified.

SENSITIVITY ANALYSIS AND COMPARISON OF ALGORITHM PERFORMANCE

Results from tests evaluating the effectiveness of the new algorithm include the main algorithm performance measures,

namely detection rate (ratio of incidents detected out of all incidents), false alarm rate (ratio of false alarms out of all decisions, incident or nonincident, made by the system), and mean time to detect (average time duration needed for detection). (Detection time is measured from the time incidents reported in the operator's log instead of from actual occurrence time).

Algorithm performance is assessed via operating characteristic curves, an evaluation method whose effectiveness lies on its independence from algorithm structure. Operating characteristic curves depict detection and false alarm rates accomplished by an algorithm across threshold values. To construct these curves, the threshold parameters are allowed to vary over a wide range of values. Every threshold set (pair) produces a performance point (P_D, P_F) on the curve.

Three types of smoothing have been considered, linear (average), median, and exponential. Past and current occupancy measurements are smoothed according to one of these types and are included in the corresponding version of the algorithm. For each type of smoothing, several alternative structures were tested by varying the number of terms in the smoothing windows or the value of the smoothing parameter, α , in the exponential version. In particular, window sizes with 5 to 20 terms for the past and 3 to 10 for the current period, and exponential smoothing factors of 0.03 to 0.10 were considered. For each algorithm type, only the structures whose parameters result in optimum performance in terms of detection and false alarms are presented. The characteristics of the selected algorithms are presented in Table 1. Threshold sets and algorithm performance measures are presented in Table 2.

To assess the performance improvement from using smoothed data instead of raw data, the performance of DELOS was compared with that of an older algorithm featuring a structure similar to DELOS. In particular, the Double Exponential algorithm is based on smoothing the surveillance data (e.g., the spatial occupancy difference between adjacent stations) according to Equations 9 and 10. Functions $S_1(t)$ and $S_2(t)$ provide a forecast of spatial occupancy difference, and an incident is signaled when the cumulative error between forecast and current measurement exceeds a threshold. To obtain comparable performance measures, the algorithm was tested on the same data set as the new algorithms.

TABLE 1 Characteristics of Smoothing Algorithms

Algorithm	Past period smoother	Present period smoother		
DELOS 1.1 (10,8)	Average,	Average,		
	length 10.	iengin o.		
DELOS 2.2 (9,9)	Median,	Median,		
	length 9.	length 9.		
DELOS 3.3 (0.05,6)	Exponential,	Exponential,		
	$\alpha = 0.05.$	α=0.05,		
		time lag 6.		
DELOS 3.1 (0.05,6)	Exponential,	Average,		
	<u>α=0.05</u> .	length 6.		

Algorithm	T _c	Tı	Detection Rate (%)	False Alarm Rate (%)	Hourly Number of False Alarms	Average Detection Time (min)
DELOS1.1	0.30	0.30	85	0.431	6.7	0.8
(10, 8)	0.40	0.40	74	0.224	3.5	1.1
	0.55	0.55	63	0.074	1.2	2.1
	0.60	0.60	48	0.053	0.8	1.6
	0.70	0.70	41	0.033	0.5	2.1
	0.80	0.80	33	0.016	0.2	1.3
DELOS2.2	0.30	0.40	78	0.361	5.6	1.4
(9, 9)	0.40	0.50	74	0.223	3.5	1.8
	0.40	0.60	59	0.137	2.1	1.8
	0.50	0.70	48	0.080	1.2	1.8
	0.60	0.80	41	0.039	0.6	1.6
	0.80	0.80	30	0.031	0.5	0.7
DELOS3 3	0.07	0.07	85	0.411	64	1.0
(0.05, 6)	0.15	0.10	78	0.176	27	11
(0.03, 0)	0.15	0.12	67	0 113	1.8	14
	0.16	0.16	59	0.059	0.9	13
	0.15	0.20	48	0.030	0.5	1.5
	0.23	0.23	33	0.014	0.5	3.2
	0.20	0.20			0.2	5.2
DELOS3.1	0.40	0.30	85	0.476	7.4	0.6
(0.05, 6)	0.50	0.40	78	0.257	4.0	1.1
	0.60	0.40	70	0.173	2.7	1.1
	0.60	0.60	63	0.084	1.3	1.1
	0.70	0.70	48	0.045	0.7	1.2
	0.80	0.80	41	0.029	0.5	1.9
	1.00	0.70	30	0.022	0.2	2.1

TABLE 2 Thresholds and Performance Results

* test site length is 8.8 km and includes 14 detector stations

$$S_{1}(t) = \alpha \left[OCC(i,t) - OCC(i + 1,t) \right] + (1 - \alpha) S_{1}(t - 1)$$
(9)

$$S_2(t) = \dot{\alpha} S_1(t) + (1 - \alpha) S_2(t - 1)$$
(10)

The two exponential DELOS algorithms are compared with the Double Exponential algorithm in Figure 5. The comparison indicates that smoothing current measurements leads to substantial reduction in false alarms.

The evaluation results for the four alternative smoothing types are shown in Figure 6. Although the performances of average and exponential smoothers are comparable, they are superior to the median algorithm. This may be attributed to the fact that median smoothers tend to better preserve data fluctuations, and this produces a higher number of false alarms.

To better appreciate the performance of the proposed algorithms, Figure 6 includes performance curves from two approaches tested here, modified California and Algorithm 7. The comparison indicates significant detection improvement of the proposed algorithms, especially at low false alarm rates that are most suitable for operational use. In particular, presenting false alarm performance in the hourly number of alarms indicates algorithm potential as an operator's primary tool for incident detection. For instance, from Table 2, the proposed algorithms, at 60 percent detection rate, yield approximately 1 false alarm per peak hour in an 8.8-km (5.5-mi) heavily traveled freeway segment with 14 detector stations. Performance may also be seen in terms of detection rate for each type of incident. Accidents, for instance, are more important to detect than stalls because they typically have a strong congestion effect and require prompt emergency assistance. To investigate the algorithm effectiveness in detecting each type of incident, detection performance of DELOS 1.1 (10,8) in detecting accidents and stalls is shown in Figure 7. The figure indicates, for example, that at approximately 1 false alarm per hour (false alarm rate = 0.07 percent) in the whole section, accident detection rate approaches 90 percent.

Regarding average detection time (Table 2), the range for the average algorithm is 1 to 2 min, for the median 1.5 to 2 min, for the exponential 1 to 1.5 min, and for the combined exponential-average 0 to 1 min. The incident occurrence times are from the operator's log. Detection time is the time between occurrence and end of the current period for which an incident alarm is signaled. Therefore, these values do not reflect actual detection times but the delay with regard to detection by the operator. This partly explains why an 8-interval forward seeking method [e.g., DELOS 1.1 (10,8)] has a detection time of 1 to 2 min instead of at least 4 min. A second reason is that, especially in severe incidents, the algorithm may start sensing occupancy changes while only part of the current window overlaps with the incident period. DELOS detection times are slightly longer than those of algorithms employing raw data. For instance, the California algorithms exhibit response times of 0 to 1 min.



FIGURE 5 Algorithm performance comparison: DELOS versus Double Exponential.

A final comment brings up a positive contribution of computerized algorithms—the reduction in missed detection. In particular, algorithms can identify incidents not detected by operators. To investigate this, the major false alarms produced by the new algorithms were examined; 22 of these exhibit incident-like patterns, including patterns that strongly resemble incidents. However, because no off-line incident identification can independently verify their occurrence, such alarms were treated as false. Further, all incidents missed by the algorithms were stalls on the shoulder and had no impact on traffic. Because they were recorded by the traffic operator,

they were classified as missed incidents. If they had been discarded, the detection rate of the new algorithms would increase substantially.

CONCLUSION

The aim of this research is to improve automatic incident detection on freeways by developing strategies to distinguish incidents from other traffic disturbances. Major disturbances identified in this paper include recurrent congestion at bottle-



FIGURE 6 Algorithm performance comparison: DELOS versus California algorithms.



FIGURE 7 DELOS detection performance by incident type.

neck locations, traffic pulses propagating downstream, compression waves propagating upstream, short-duration random fluctuations, and impulsive noise in the traffic measurements.

An incident detection logic was developed within the framework of comparative algorithms (i.e., algorithms that employ simple comparisons of traffic data). The detection logic attempts to distinguish incidents from other disturbances based on two major incident characteristics—fast evolution of congestion following incidents and long duration of incident patterns. To distinguish sharply evolving incident congestion from gradually developing recurrent congestion, temporal comparisons of traffic patterns were performed. Further, to filter out short-duration traffic disturbances, several types of data smoothing were employed. The smoothing algorithms effectively filter short-duration traffic inhomogeneities, such as random traffic fluctuations and traffic pulses, but do not adequately handle compression waves of long duration.

The proposed algorithms were tested with loop detector data from I-35W in Minneapolis with promising results (for instance, 1 false alarm per rush hour per 14 detector stations at approximately 60 percent detection rate). They were also compared with major algorithms used for assisting incident management personnel in urban areas and were found to be superior at all false alarm rates.

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