parking is a non-capital-intensive improvement that is well suited to use as a TSM strategy. This improvement is being used in local corridors and busy intersections or blocks to improve traffic flow. However, certain parking strategies have both short-range TSM and long-range planning aspects. For example, street parking can be eliminated at little cost, and this will improve local traffic flows and reduce accidents. However, when substantial amounts of on-street parking are eliminated, most cities have to provide additional off-street parking. This procedure is usually expensive, ranging from the purchase of land to the construction of parking garages, and takes considerable time to plan and implement. Thus, this strategy is more suited to use as a long-range planning element.

The majority of parking strategies are, in fact, long-range planning elements. For example, a freeze on the number of parking spaces within a city would take considerable planning to implement to ensure that mobility and the economic life of the affected area were maintained. These improvements, although not necessarily capital intensive, would require complementary strategies that, for the most part, would be expensive.

CONCLUSIONS

The environmental, economic, and energy issues of recent years have caused new emphasis to be placed on using parking management strategies to reduce automobile travel and increase the use of public transportation. Based on a review of the literature and the results of a survey questionnaire of U.S. cities, the following conclusions are offered.

1. Parking management strategies are not widely used on an areawide basis.
2. Parking strategies in the realm of TSM actions include (a) providing short-term parking, (b) eliminating on-street parking, and (c) strictly enforcing parking regulations. Most other strategies can have a dramatic effect on an urban area and are being implemented carefully over a long period of time. Thus, some parking strategies are short-range in nature and others are more appropriately part of the long-range element.
3. Parking strategies generally have diverse effects on an urban area. For example, encouraging short-term on-street parking may attract shopping trips and help revitalize the central business district. However, this will increase overall vehicle kilometers of travel, which will counter attempts to reduce air pollution and conserve energy.
4. There have been very few attempts to evaluate the effectiveness of parking controls, and little is known about the interrelationships between parking management strategies and supporting services.
5. There are few legal problems associated with implementing parking controls; however, public, political, and business opposition act as a deterrent to their implementation.
6. The use of parking policies to improve air quality, conserve energy, or attain other national goals may not achieve beneficial results in many urban areas, but could produce strong public opposition and cause economic decline of the central city.
7. In most cities, there is no perceived local problem that would require the extensive use of parking regulations to limit automobile travel.
8. Parking management policies may have beneficial effects in urban communities if they are applied gradually to alleviate local problems and promote achievement of local planning goals.

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Freeway Incident-Detection Algorithms Based on Decision Trees With States

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Incident-detection algorithms are a part of an overall freeway-traffic management system. These algorithms provide indications of the probable presence of freeway incidents by processing electronic surveillance data. In this paper, a class of algorithms that are designed to discriminate patterns in the data peculiar to incidents are described. The generic structure of these algorithms is the decision tree with states, the states corresponding to distinct traffic conditions. Ways to calibrate algorithm thresholds are described and applied to the algorithms. Performance evaluations based on traffic data from the Los Angeles system are presented.

An important function of freeway traffic management is the detection of and response to freeway incidents. Past research (1, 2) and operating experience have demonstrated that the detection of incidents can be automated through the use of specific incident-detection algorithms that operate on electronic surveillance data to produce indicators of the probable presence of an incident. The previously developed algorithms, however, are less effective than is desirable for operational use because they generate a high level of false alarms. This paper describes several new algorithms that are based on a generalization of the structure of the California algorithm, the decision tree with states, and that have been demonstrated to have significantly improved performance through evaluations based on a large amount of real surveillance data.

The results reported here represent a portion of the results obtained in the study; they are more fully reported elsewhere (3, 4, 5, 6, 7, 8) and have also been summarized (9).

The study was empirical in nature, being based entirely on a large amount of data obtained from the Los Angeles and Minneapolis freeway surveillance systems. In all, more than 10 000 000 vehicle-sensor crossings and approximately 150 incident events were used in the developments and evaluations. This is by far the most extensive data base ever used in research on incident-detection algorithms. Although more detailed data were available from the Los Angeles system, the data used in the algorithms were 20- and 30-s occupancies and volumes, averaged over all lanes at a station.

The research involved, first, an evaluation of previously developed algorithms (3). This evaluation indicated the superiority of occupancy-based algorithms, especially those that use occupancy values at adjacent stations on the freeway. Algorithms based on double exponential smoothing were among the best found, but the multiplicity of incident indications they generated was deemed to be an operational disadvantage. Subsequent evaluations (5) established that the California algorithm is the best of these, in that its detection-false alarm performance is best and, moreover, the incident indication was consistently associated with the actual location of the incident. This result contradicts earlier findings (1). A detailed examination of these earlier findings and our findings, however, showed that the bases for the conclusions were different. Generally, our findings emphasized detection rate performance at much lower false-alarm rates.

The results of these evaluations were used for the principal portion of the study, that of developing and evaluating new algorithms (which is the subject of this paper). The development of new algorithms initially followed two paths. The first, which was based on a complex, time-series approach (5), did not provide effective algorithms for the heavier traffic regimes that were our principal concern, but it does hold promise for light-to-moderate traffic regimes. The second path was based on extensions to the structure of the California algorithm.

Further attention was given to the effects of geometrics, sensor configurations, malfunctioning sensors, and weather and to means for identifying the lane of the incident (5).

The next section of this paper describes and analyzes the California algorithm and introduces the decision tree with states as a generic structure for several new incident-detection algorithms. Following this, we define the measures of performance, and detection and false-alarm rates and describe how the multiple thresholds in an algorithm can be calibrated to give an optimum trade-off curve in terms of these measures.

The several new algorithms and one old one are introduced after a discussion of the patterns in traffic data whose identification played a major role in the development of the new algorithms. Performance evaluations are presented for these algorithms.

CALIFORNIA ALGORITHM

As a preliminary to the introduction of decision trees with states as a general structure for incident-detection algorithms, we will describe the structure of the California algorithm and how its elements relate to patterns in traffic data. Of all previously defined incident-detection algorithms, the California algorithm is clearly superior (3, 5). Furthermore, the California algorithm, as compared with other algorithms, has the unique characteristic that three functions, rather than a single one, of the traffic data are used and that these functions (or features as we will henceforth refer to them) are selected to distinguish, in combination, patterns in the traffic data specifically related to incidents.

The several features—OCC, DOCC, OCCDF, OCCRDF, and DOCCTD—that are used in the California and the other algorithms to be described here are defined below [station indexes (i) increase in the direction of travel].

Feature	Description	Definition
OCC(i, t)	Occupancy at station i, for time interval t (percent)	
DOCC(i, t)	Downstream occupancy	OCC(i + 1, t)
OCCDF(i, t)	Spatial difference in occupancies	OCC(i, t) - OCC(i + 1, t)
OCCRDF(i, t)	Relative spatial difference in occupancies	OCCDF(i, t)/OCC(i, t)
DOCCTD(i, t)	Relative temporal difference in downstream occupancy	[OCC(i + 1, t - 2) - OCC(i + 1, t)] / OCC(i + 1, t - 2)

All features involve only the use of occupancy, measured as the average over all instrumented lanes at a single location on the freeway and over a 1-min interval.

Algorithms based on features involving volume and the volume-to-occupancy ratio were also investigated but were generally found to be inferior (3).

The California algorithm is described in Figure 1. This algorithm, as originally defined, used in place of DOCCTD a similar feature in which OCC (i+ 1, t - 5) replaced OCC (i+ 1, t - 2) as it appears in the definition of DOCCTD given above. The latter version is sometimes referred to as the modified California algorithm. It is seen that three features are used that have three corresponding thresholds. This algorithm is an example of a decision tree. The algorithm is executed in a sequence of steps, starting at the top, or root node (see Figure 1). The first test is made, and a branch to the left (OCCDF $\geq T_1$) or right (OCCDF $< T_1$) is followed. In this instance, a branch to the right yields a final designation of incident-free conditions, which are coded here as a state value of 0. Otherwise, subsequent tests are made in a similar manner, until a final designation of incident or incident-free is made.

This algorithm is executed for each adjacent pair of sensor stations, i.e., for sections of the freeway bounded by the sensor stations, at regular intervals of 20 s (as in Los Angeles), 30 s (as in Chicago and Minneapolis), or 1 min (as in our study).

The structure of the California algorithm derives from a consideration of the pattern of traffic data that typically arises when an incident occurs. An example of this pattern is given in Table 1, which uses actual values of occupancy taken from the Los Angeles system. The pattern that develops can be explained on a theoretical basis, but it is sufficiently evident that here we appeal only to driving experience and simple facts. The incident reduces the capacity of the freeway at the site of incident. If the resultant capacity is less than the volume of traffic upstream, congestion builds up (i.e., queueing develops); the boundary of the congested region propagates in an upstream direction on the freeway at a typical speed of 8 to 16 km/h (5 to 10 mph) (although this speed depends on the particular values of the capacity at the site and the upstream volume). The congested area includes the upstream sensor stations in an orderly sequence following the occurrence of the incident.

Downstream of the site of the incident, the freeway

Figure 1. California algorithm.

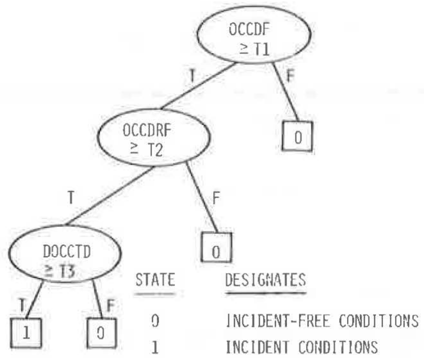


Table 1. Occupancy values: incident data set 74051501, Santa Monica Freeway eastbound.

	1-Min Occupancy at Station[a]						
Time	**21**	**22**	**23**	**24**	**25**	**26**	**27**
7:05	15	17	15	16	16	17	15
7:06	15	18	13	13	15	16	15
7:07	16	16	15	15	15	15	14
7:08	14	17	17	15	17	15	15
7:09	15	17	17	16	16	15	16
7:10	16	18	18	19	15	15	14
7:11	17	17	19	17	16	16	15
7:12	18	19	15	17	18	15	15
7:13	15	19	17	16	20	18	20
7:14	16	17	17	17	18	18	25
7:15	18	19	18	16	17	20	21
7:16	18	17	17	18	19	15	23
7:17	17	21	17	19	21	14	17
7:18	14	20	19	17	43	10	19
7:19	15	21	20	30	33	10	11
7:20	14	18	18	47	32	10	13
7:21	14	16	34	30	29	9	11
7:22	16	14	30	38	37	12	10
7:23	15	19	21	37	32	10	10
7:24	15	27	20	46	33	11	9
7:25	17	37	27	35	36	11	11
7:26	25	32	43	30	32	12	11
7:27	26	20	26	33	40	11	12
7:28	44	20	20	42	44	12	10
7:29	37	38	20	40	30	15	11
7:30	27	42	28	41	25	14	14
7:31	26	32	37	30	27	14	14
7:32	34	25	29	29	37	11	12
7:33	30	22	33	43	27	14	12
7:34	28	35	37	32	24	13	13
7:35	26	44	38	32	22	12	12
7:36	35	28	28	29	22	14	13
7:37	54	33	27	30	29	12	14
7:38	35	42	23	29	30	12	13
7:39	30	37	21	41	29	13	13
7:40	49	31	24	36	40	14	13

Note: Incident occurred at 7:15:40 between stations 25 (upstream) and 26 (downstream).
[a]Station indexes increase in direction of travel.

is cleared of traffic; the boundary of the cleared region propagates downstream at a speed that may be as high as 80 km/h (50 mph).

Thus, an incident creates, after some interval of time, a significant difference in occupancy values at the sensor stations bounding the site of the incident. The features OCCDF and OCCRDF are intended to measure this effect. Two features are used (rather than OCCRDF alone, for example) to avoid problems in light traffic where OCCRDF might be briefly large due to normal fluctuations in traffic data.

However, other normal conditions can also produce significant differences in occupancy values. Geometric bottlenecks are a frequent source of such differences. The occurrence of an incident can often be distinguished by the fact that the downstream occupancy decreases rather abruptly, so that the feature DOCCTD would have, briefly, an unusually large value. This is the third feature used in the California algorithm.

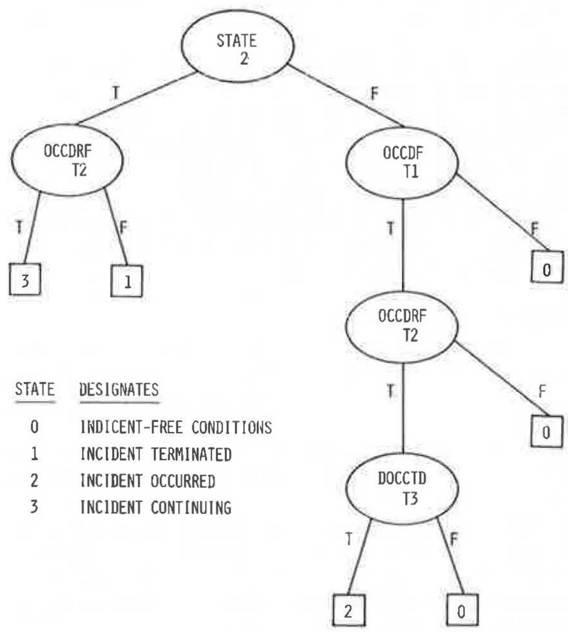
DECISION TREES WITH STATES

In freeway operations, it is desirable not only to detect the occurrence of an incident, but also to know when it has terminated. A simple means for accomplishing this is to augment the California algorithm in the manner suggested in Figure 2. Note that we now make use of four state values: 0 corresponds to incident-free conditions, 1 corresponds to termination, 2 corresponds to the initial detection of the incident, and 3 corresponds to the continued presence of incident conditions. The state values are retained for each section and used in the subsequent application of the algorithm. For example, Figure 2 shows that the first test in the algorithm is state ≥2. This is a decision tree with states.

We have found this general structure to be useful in a variety of ways; many more state values can be identified to provide a more refined classification of the traffic condition.

Any algorithm based on a decision tree can be defined by a data structure and a general algorithm for running down the tree. As a result, such algorithms are very easy to implement and extremely fast to execute. De-

Figure 2. Refinement of California algorithm (algorithm 2): example of decision tree with states.



tails of these matters are beyond the scope of this paper, but can be found elsewhere (5, 6, 7).

PERFORMANCE MEASURES AND THRESHOLD CALIBRATION

Up to this point, we have been concerned with features and the algorithm structure. Completion of the specification of an algorithm requires specification of the set of thresholds, e.g., T_1, T_2, and T_3 in Figure 1. As previously implemented, the thresholds for the California algorithm were determined by a trial-and-error process. A commonly used set is $T_1 = 8$, $T_2 = 0.5$, and $T_3 = 0.15$. Our purpose here is to describe a systematic threshold-calibration technique. This technique is designed to yield optimal performance as measured by false-alarm and detection rates.

Four possibilities arise when an incident-detection algorithm is executed, as indicated below.

Condition Indicated by Algorithm	Actual Condition	
	Incident-free	Incident
Incident-free	–	Missed detection
Incident	False alarm	Detection

By accumulating the results over a number of tests and defining N_F = total number of tests performed by the algorithm and N_{FA} = total number of false-alarm signals generated by the algorithm, we can compute the false-alarm rate as

$$\alpha = \text{false-alarm rate (percent)} \equiv 100 \times N_{FA}/N_F \qquad (1)$$

Next, by defining N_I = number of incidents and N_D = number of incidents detected, we have

$$\beta = \text{detection rate (percent)} \equiv 100 \times N_D/N_I \qquad (2)$$

To determine that a valid detection has been made, we must define the spatial and temporal deviations allowable between the actual incident event and the detection event. Our assessments required detections in a time interval beginning 5 min before and ending 20 min after the estimated time of occurrence and corresponding to the actual section on which the incident occurred or the next downstream section.

Other measures are also of interest, e.g., the mean time to detect but, in the interest of brevity, we shall confine our attention in this paper to the measures defined above. Information pertaining to the mean time to detect can be found elsewhere (5).

The false-alarm and detection rates clearly depend on the choice of threshold set, which we will denote as a whole by T. Suppose there is a requirement on the detection rate; if an allowable threshold set T is one for which $\beta(T) \geq y$, y is the minimum detection rate specified. Of all such threshold sets, the best one is that which minimizes the false-alarm rate. This leads to consideration of the problem

$$\min_T \{\alpha(T) | \beta(T) \geq y\}$$

The solution of this problem yields a threshold set $T^*(y)$, a detection rate $\beta[T^*(y)] \geq y$, and a false-alarm rate $\alpha[T^*(y)]$. By varying the parameter (y), one obtains corresponding threshold sets and false-alarm rates. Threshold calibration is thus reduced to a sequence of constrained minimization problems, where the functions involved [$\alpha(T)$ and $\beta(T)$] are defined by application of the algorithm to the available data. This procedure was mechanized in our study and used extensively to produce threshold sets. Details of the procedures and software are available elsewhere (5, 7).

Note the inherent trade-off: as the requirement on the detection rate is increased, the corresponding best false-alarm rate is also increased. The results of the calibration are therefore in the form of a trade-off curve.

PATTERNS IN TRAFFIC DATA

In the course of developing and evaluating incident-detection algorithms, we have discovered that certain types of patterns in the traffic data appear repeatedly and have developed an understanding of traffic conditions that provides rational explanations for the appearance of such patterns. In this section, we describe and rationalize these patterns so that the directions used in the development of the algorithms can be more easily understood.

Incident Patterns

Depending on the nature of an incident and the traffic conditions prevailing at the time, the pattern that the traffic data develop in the presence of that incident may be one of five types.

The first type is the most distinctive in that it is the most easily discriminated from patterns associated with incident-free conditions. This pattern occurs when the capacity at the site of the incident is less than the volume of oncoming traffic so that a queue develops upstream. Simultaneously, a region of light traffic develops downstream. An example of this pattern is illustrated by the occupancy data given in Table 1. This pattern is clearest when traffic is flowing freely before the incident occurs.

The second type of pattern occurs when the prevailing traffic condition is freely flowing but the impact of the incident is less severe (for example, as might result from a lane blockage that yields a capacity at the site of the incident that is greater than the volume of oncoming traffic). This situation is more difficult to distinguish from certain incident-free patterns and, therefore, may not result in a detection.

The third type of pattern occurs, again, in freely flowing traffic, but the impact of the incident is not noticeable in the traffic data. This may occur when the incident is a disabled vehicle in the median. Incident-detection algorithms cannot be expected to detect incidents of this sort.

The fourth type is one that occurs in heavy traffic when the capacity at the incident site is less than the volume (and the capacity) of traffic downstream. This difference leads, generally, to a clearance in the region downstream of the incident. Here the traffic pattern evolves rather slowly, and a distinguishable pattern develops only after several minutes. Obviously, a very severe incident in which several lanes were blocked would result in rapid development of the pattern, but the more typical situation is one involving a slowly developing pattern.

The fifth type occurs in heavy traffic in which the capacity at the site of the incident is not less than the downstream volume. The effects are then localized and are not noticeable in the traffic data. Incident-detection algorithms cannot be expected to detect incidents of this sort.

Patterns in Incident-Free Traffic That Tend to Produce False Alarms

Four types of patterns occur under incident-free conditions that are similar to incident patterns and therefore tend to produce false alarms. The first of these is that related to malfunctioning detectors (5).

The second type arises in heavy traffic in which individual vehicles experience significant speed variations. This phenomenon shows up in traffic data in the form of compression waves that propagate in a direction counter to the flow of traffic. Several such waves can be seen in the occupancy data given in Table 2. An examination of these data shows significant station-to-station differences in occupancies of the same magnitude as is seen in patterns related to incidents. This pattern is the most significant contributor to false alarms for algorithms identified before our work (at least as measured with respect to the Los Angeles data).

The third is associated with abnormal geometrics, for example, that which is found at freeway-to-freeway interchanges.

The fourth is associated with bottlenecks (for example, at locations that have a substantial volume of on-ramp traffic). These bottleneck locations are such that the total demand exceeds the capacity of the freeway. Examples of these latter two types of patterns are given elsewhere (5).

Consequences for Algorithm Development

It should be evident from this disucssion that effective incident-detection algorithms require more than an identification of a discontinuity in the traffic data—there are numerous such occurrences in incident-free data. The algorithms we have developed explicitly account for the differences in the detailed nature of the discontinuities found in the traffic stream under incident and incident-free conditions. Our developments have led to algorithms that can always detect the first type of incident pattern and can sometimes detect the second and fourth. At the same time, certain algorithms have been developed that are invulnerable to compression waves.

Incidents in light traffic are not generally detected by the algorithms we have developed. Tignor (10) has investigated the application of single-exponential smoothing to the detection in this regime. Another potentially effective means for detecting such incidents involves the use of traffic correlation and is discussed elsewhere (5).

SEVERAL NEW ALGORITHMS

The algorithm depicted in Figure 2 is a slight modification of the California algorithm. We now wish to turn to descriptions of several new algorithms that have been developed to discriminate more effectively, based on a qualitative assessment of patterns in traffic data, and that have, in fact, been found to have superior performance. In all, our research yielded 10 algorithms (including, essentially, the California algorithm and 2 simple variants). Our discussion here will be limited to a discussion of two of these, which for consistency with the references cited are denoted as algorithm 7 and algorithm 8.

Many—but not all—disturbances in incident-free traffic are short-lived and, although they may produce an incident signal, the associated incident-continuing state value does not last long (if it is produced at all). This is in contrast to the majority of incidents that produce a discontinuity in the traffic stream that generally lasts at least several minutes. Thus, it has been suggested that improved performance might be obtained by requiring that the discontinuity persist for a period of time.

The state feature of the binary-tree structure we have adopted provides a convenient way to include a persistence requirement. In its simplest form, one sets the state value equal to, for example, 1 when a discontinuity is first detected and then signals an incident (state value equal to, for example, 2) if the next test (for that station or section) indicates that the discontinuity has persisted.

Algorithm 7, which is illustrated in Figure 3 and has the same state values as algorithm 2, incorporates this persistence requirement and involves replacement of DOCCTD by DOCC, the occupancy at the downstream station. This choice is based on the observations that (a) the most common cause of false alarms in the California algorithm is a compression wave that moves in a direction counter to the flow of the traffic and (b) in heavy traffic that has compression waves, the downstream occupancy rarely drops below 20 percent (in the Los Angeles data), whereas incidents generally produce downstream occupancies substantially less than 20 percent.

The application of the threshold-calibration methodology described above yielded the performance measures and threshold sets given in Table 3.

Compression waves in heavy traffic are a principal source of false alarms, and some success in eliminating such false alarms is obtained by using algorithm 7. Further efforts to improve performance in heavy traffic involved attempting to account for the regularity in the pattern of traffic associated with compression waves.

Consider the data given in Table 2 for an incident-free data set. As we have noted, compression waves are manifested by sudden large increases in occupancy that move through the traffic stream in a direction counter to the direction of travel. Attempts were made to account for this pattern through the use of correlation analysis (5), but the patterns were not sufficiently regular for this technique to be successful.

Therefore, we considered a more gross way to account for the observed patterns. As Table 2 shows, a large increase at one station is typically followed some 2 to 5 min later by a large increase at the next station upstream. The typical station spacing in Los Angeles is 0.8 km (0.5 mile), corresponding to a shock wave speed of 9.7 to 24 km/h (6 to 15 mph). The fact that a compression wave has passed over a station can be captured by the simple test shown in Figure 4, where $T_5 = 30$ and $T_2 = -0.250$ have been found to be effective.

Of course, incidents also produce patterns that would yield positive results for this test. In heavy traffic that has compression waves, one would expect that a positive result for this test would be followed, typically within 5 min, by a positive result at the next station upstream. Thus, incidents are distinguished by the absence of a compression wave at the downstream station in the previous 5 min.

Algorithm 8, which is shown in Figure 5 and has state values as defined below, uses the state feature in an unusual way.

State	Designates
0	Incident-free
1	Compression wave downstream in this minute
2	Compression wave downstream 2 min ago
3	Compression wave downstream 3 min ago
4	Compression wave downstream 4 min ago
5	Compression wave downstream 5 min ago
6	Tentative incident
7	Incident confirmed
8	Incident continuing

Essentially, this algorithm suppresses incident detection at any station for a period of 5 min after detection of a compression wave at the downstream station. This algorithm, which has both a persistence requirement and a continuing incident state, may appear to be com-

Table 2. Occupancy values: incident-free data set 74090454, San Diego Freeway southbound.

Time	1-Min Occupancy at Station[a] 32	31	30	29	28	27	26
7:10	15	20	20	18	22	26	22
7:11	13	21	19	18	22	28	26
7:12	16	19	20	19	21	32	26
7:13	13	18	16	18	30	25	25
7:14	14	22	17	18	25	23	24
7:15	14	20	20	26	44	29	26
7:16	14	18	18	25	34	26	24
7:17	13	21	19	36	26	21	25
7:18	14	24	21	48	29	25	21
7:19	16	26	32	28	31	26	25
7:20	21	24	47	19	26	39[b]	23
7:21	14	26	32	27	26	21	22
7:22	14	52	32	22	29	19	23
7:23	14	27	23	20	50[b]	18	24
7:24	13	26	21	21	30	22	26
7:25	24	21	22	62[b]	23	26	24
7:26	39	20	23	38	23	28	23
7:27	23	21	65[b]	29	22	30	23
7:28	26	24	43	28	23	23	25
7:29	31	26	26	29	22	30	23
7:30	30	60[b]	22	35	22	24	23
7:31	31	41	21	30	17	26	24
7:32	37	29	27	26	23	18	26
7:33	50[b]	26	35	22	37	22	24
7:34	53	22	31	21	29	26	26
7:35	48	21	32	21	25	22	23
7:36	29	28	33	39	21	24	23
7:37	37	33	28	26	22	30	27
7:38	38	29	44	21	20	23	24
7:39	40	25	38	21	21	20	27
7:40	53	23	43	19	30	23	24
7:41	37	47	44	22	36	26	23
7:42	41	30	42	23	38	28	26
7:43	38	26	38	21	31	22	25
7:44	56	24	29	33	29	23	22
7:45	64	25	24	38	27	27	24

[a] Station indexes increase in direction of travel.
[b] Large-occupancy value indicative of compression wave.

Table 3. Thresholds and performance results.

Algorithm	T_1	T_2	T_3	T_4	T_5[a]	Detection Rate (%)	False-Alarm Rate (%)
2	5.4	0.325	0.011			82	1.341
	6.8	0.307	0.056			71	0.883
	15.0	0.335	-0.050			61	0.346
	9.9	0.552	-1.112			51	0.169
	9.5	0.629	-1.746			41	0.064
	21.3	0.646	-2.080			31	0.026
	29.9	0.685	-1.959			20	0.011
7	8.1	0.313	16.8			59	0.134
	12.9	0.360	16.6			51	0.050
	13.1	0.358	15.8			49	0.043
	9.6	0.359	12.3			41	0.029
	13.1	0.393	12.5			37	0.017
	21.6	0.301	13.9			31	0.006
	26.6	0.322	13.4			20	0.004
8	10.2	-0.443	0.312	28.8	30	61	0.177
	13.1	-0.296	0.309	15.9	30	51	0.038
	18.1	-0.310	0.356	18.5	30	41	0.024
	5.2	-0.401	0.590	27.9	30	31	0.010
	24.4	-0.392	0.579	13.0	30	20	0.003

[a] Held fixed.

plex because it involves 21 decision nodes, but its components have straightforward interpretations (5).

Application of the threshold calibration methodology yielded the performance measures and threshold sets given in Table 3.

ONE OLD ALGORITHM

To compare the new algorithms with a popular approach to the construction of incident-detection algorithms—double exponential smoothing—we include here a brief description of one further algorithm, designated algorithm 11 (5). This was the best performing of this type of algorithm that we considered. The basis for this type of algorithm is the smoothing of surveillance data, e.g., OCCDF(t), according to

$$S_1(t) = \alpha \text{OCCDF}(t) + (1 - \alpha)\, S_1(t - 1) \tag{3}$$

and

$$S_2(t) = \alpha S_1(t) + (1 - \alpha)\, S_2(t) \tag{4}$$

These derived functions, $S_1(t)$ and $S_2(t)$, are used to provide a forecast, e.g., of OCCDF(t), and the accumulated forecast error is then used as the basis for the algorithm.

Results of calibration and evaluation of algorithm 11 are given below.

Threshold	Detection Rate (%)	False-Alarm Rate (%)
-3.29	71	0.705
-3.88	61	0.373
-4.52	51	0.200
-5.06	41	0.126
-6.14	31	0.048
-7.52	20	0.021

COMPARISON OF ALGORITHM PERFORMANCE

Algorithms 2 and 11 are compared in Figure 6 on the bases of detection and false-alarm rates. At higher false-alarm rates, algorithm 11 has a slight advantage; at lower false-alarm rates, suitable for most operational purposes, algorithm 2 is clearly superior.

Figure 3. Decision tree for algorithm 7.

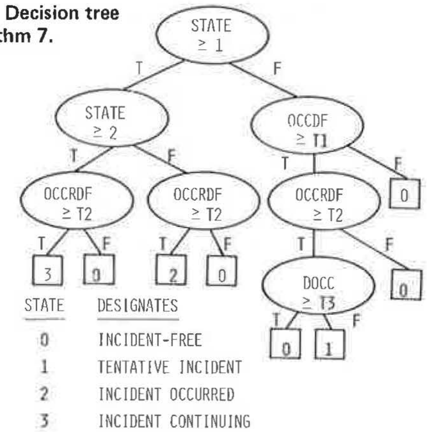
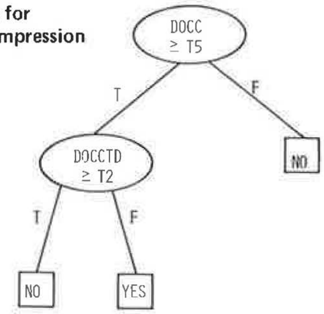


Figure 4. Test for presence of compression wave.



To provide an independent evaluation of algorithm performance, the ability of algorithms 2, 7, and 8 to detect incidents in an expanded data base involving 118 incidents was tested. (A data base with 50 incidents was used for the calibration). The results are shown in Figure 7. Algorithm 8 is generally superior, because of its superior handling of compression waves (present in much of the Los Angeles data); algorithm 7 gives somewhat poorer performance (but it is much simpler); and the California algorithm, algorithm 2, generally gave the poorest performance.

These relative performances held up when tested by using data taken from the Minneapolis system, thus providing evidence for the transferability of the research results to other freeway surveillance systems.

CONCLUSIONS

In this paper we have discussed the advantages associated with using (a) the persistence and (b) the shock-

Figure 5. Decision tree for an equivalent form of algorithm 8.

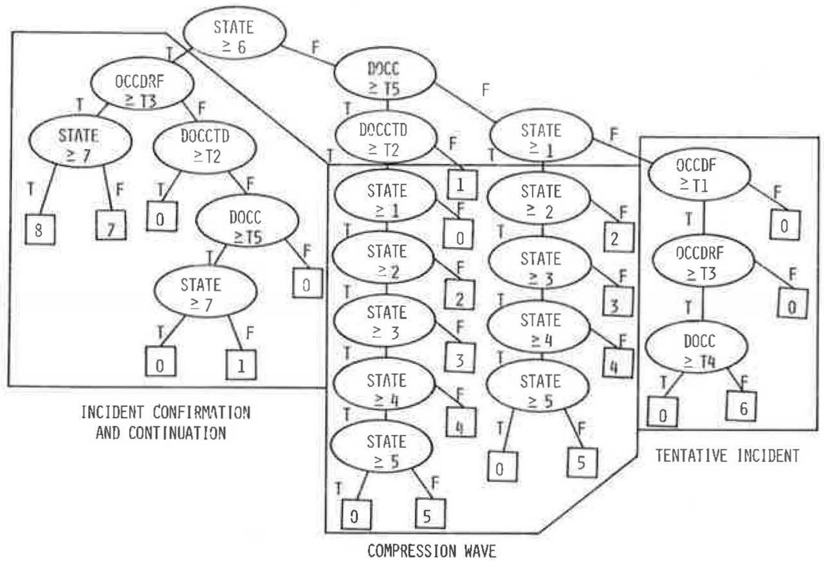


Figure 6. Comparison of performance: algorithms 2 and 11.

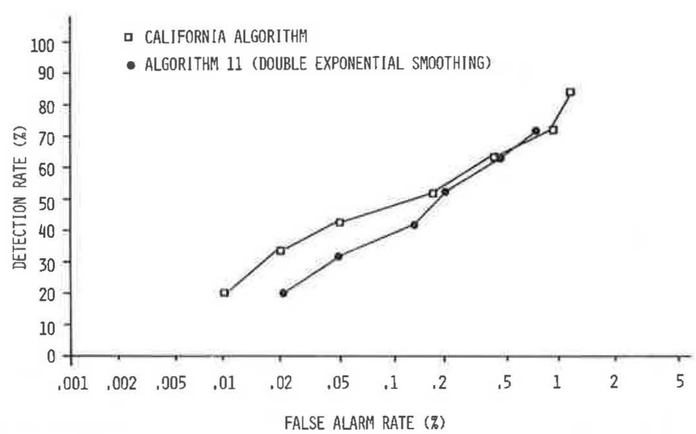
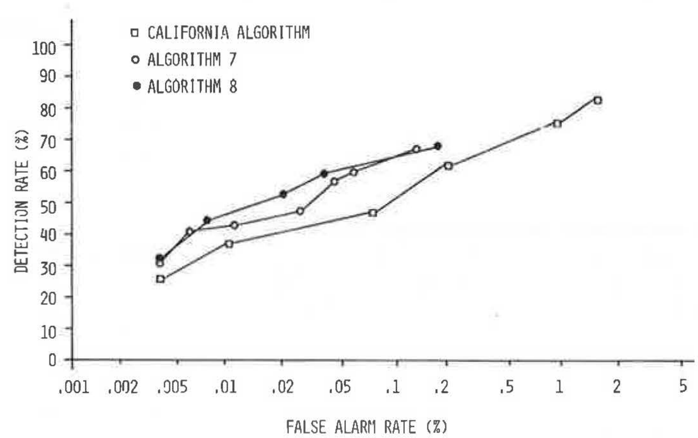


Figure 7. Comparison of performance: algorithms 2, 7, and 8.



wave detection capabilities to limit the occurrence of false alarms. These capabilities were built into two new incident-detection algorithms that are identified as algorithm 7 and algorithm 8; they have been shown to provide performance that is superior to that of the most commonly, previously used algorithm—the California algorithm.

Both algorithms 7 and 8 are primarily intended for use during moderate to heavy traffic (as are most previously developed incident-detection algorithms). Detection of incidents under low-volume conditions has been and continues to be an unresolved problem. Although it is sometimes important to be able to detect incidents at times of low volume, the greater need is for good incident-detection algorithms in moderate-to-heavy traffic conditions. It is during these times that traffic management is seriously hampered by undetected incidents. These algorithms can be implemented by using FORTRAN (6).

In the course of this work, we also identified an alternative approach for the construction of incident-detection algorithms for low-volume applications. This approach is based on the use of a traffic-correlation analysis (5). Based on preliminary results, it appears that traffic correlation is most consistent in the light-to-moderate volume regime at speeds of about 80 km/h (50 mph). However, additional work will be required before this approach can be implemented.

We also investigated ways to identify the lane(s) in which an incident had occurred (5). The lane location is important from the point of view of communicating specific information to drivers via changeable message signs or radio and also from the point of view of using appropriate ramp-control strategies for managing the freeway disturbance. The lane-location algorithm, which was effectively tested on the data base available, also appears to be potentially useful in reducing the frequency of false alarms in bottlenecks. The actual use of the lane-location algorithm for this slightly different purpose has not been attempted to date; however, we believe it offers considerable merit and should be considered in future research on this subject.

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Field Evaluation of Messages for Real-Time Diversion of Freeway Traffic for Special Events

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This paper presents the results of special-event route-diversion studies conducted in Dallas to evaluate 14 primary-candidate real-time messages that had resulted from extensive human-factors laboratory studies. The messages were displayed on matrix signs located on the freeway. The re-