Development of Freeway Incident-Detection Algorithms by Using Pattern-Recognition Techniques

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Two incident-detection experiments were conducted on the Queen Elizabeth Way Freeway Surveillance and Control System in Ontario. A pattern-recognition approach was applied to improve incident-detection algorithms. By considering the true- and false-incident-alarm identification process as pattern-recognition in nature, the maximum-likelihood decision principle was applied to develop an optimum incident-duration persistence test. The false-alarm rate fell from 0.09 to 0.06 percent during a nine-month field test experiment. In the second experiment a two-layer committee-machine structure achieved an 85.7 percent detection rate on 28 samples of historical incident data.

This paper presents the findings of two incident-detection experiments that were based on pattern-recognition concepts and carried out on the Queen Elizabeth Way (QEW) Freeway Surveillance and Control System (FSCS) (1).

This system includes an electronic incident-detection system that employs a modified California algorithm (2). It has achieved an 85 percent detection rate with a 0.09 percent false-alarm rate. To further enhance the effectiveness of this system, two incident-detection improvement experiments were conducted with historical data from QEW. In the first experiment, a pattern-recognition process was used to improve the incident-detection false-alarm rate. In the second experiment, a two-layered committee-machine concept was developed to implement a freeway-lane incident-detection algorithm.

INCIDENT-DETECTION PERSISTENCE-TEST ALGORITHM

The performance of an incident-detection algorithm is usually evaluated in terms of three measures of performance: detection rate, false-alarm rate, and detection time (3). This section examines the feasibility of improving the false-alarm rate by a pattern-recognition approach (4).

Pattern-Recognition Approach

Essentially, the problem is to discriminate between true and false alarms on the basis of their different duration characteristics. One can consider this as a pattern-recognition process whose alarms fall into either of two different pattern categories; true alarms (category 1) or false alarms (category 2).

To illustrate, consider the typical true- and false-alarm duration probability distributions shown in Figure 1. The large overlap of the two distributions indicates that there is poor pattern separability if one relies solely on alarm duration to distinguish between true and false alarms.

If, however, one considers the alarm duration pattern feature only up to a certain value, X' say, then one can use Bayes' optimal decision rule to determine an X' that will maximize the likelihood that an alarm with a duration less than X' is a false alarm. The value of X' so determined can then be incorporated into an incident-detection algorithm in the form of a persistence test to reduce the false-alarm rate. The penalty for the improvement will be an increase in the detection time of X' minutes. Bayes' optimum decision rule can be stated as follows:

$$P(I|X) = [P(X|I)P(I)]/P(X) \qquad (1)$$

where

- I = the pattern category ($I = 1$ for a true-alarm pattern and $I = 2$ for a false-alarm pattern);
- X = the pattern feature, defined only in $0 \leq X \leq X'$;
- $P(X|I)$ = the probability of occurrence of pattern X given that it belongs to category I;
- $P(I)$ = the a priori probability of occurrence of category I;
- $P(X)$ = the a priori probability of occurrence of pattern X; and
- $P(I|X)$ = the probability of occurrence of category I given that it belongs to pattern X.

The likelihood ratio, which must be maximized with respect to X', is given by

$$LR = P(2|X)/P(1|X) \qquad (2)$$

If this is greater than unity then pattern X can be categorized as belonging to a false-alarm pattern category according to the maximum-likelihood decision principle.

Duration of Persistence Test Interval

To illustrate the application of the above approach for improving incident-detection performance, we shall consider the historical incident-detection data collected on the QEW over a 14-month period from January 1977 to February 1978. The data are shown plotted as histograms in Figures 2 and 3 for true- and false-incident-alarm conditions, respectively. In each figure, the frequency of occurrence of the alarm condition within prescribed alarm duration intervals is indicated. If alarm duration can be considered as a random variable, then the probability of a sample alarm condition occurring within a given alarm duration interval is approximately equal to the number of samples in that interval divided by the total number of samples.

The data in Figures 2 and 3 can be used directly to calculate the likelihood ratio. For example, if we assume a value of $X' = 1$ min, then we have

$$P(X|I = 1) = (1 + 2)/89 = 0.0337$$
$$P(X|I = 2) = (103 + 78)/485 = 0.373$$
$$P(1|X) = 0.0163$$
$$P(2|X) = 0.984$$

which indicates that only 1.6 percent of the alarm patterns occurring within an alarm duration interval of 1 min are true alarms.

Then the likelihood ratio is given by

Figure 1. Typical alarm duration probability distributions.

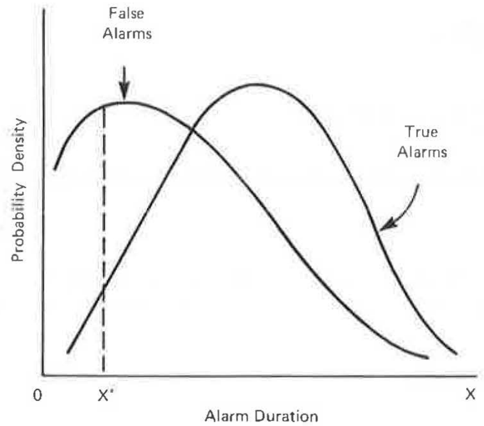


Figure 2. True-alarm duration histogram.

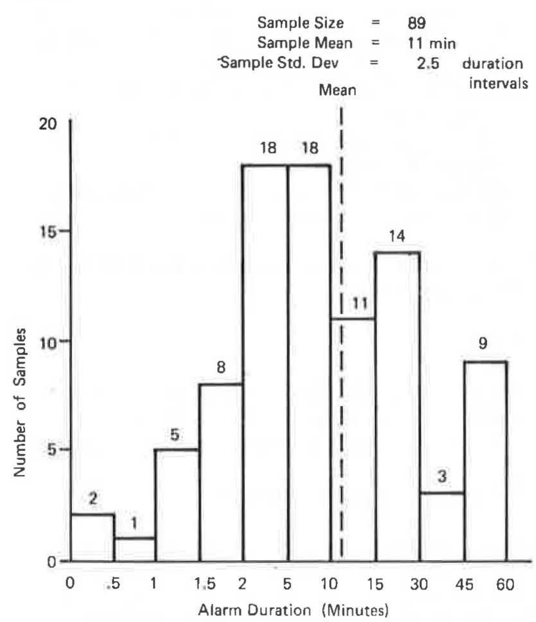
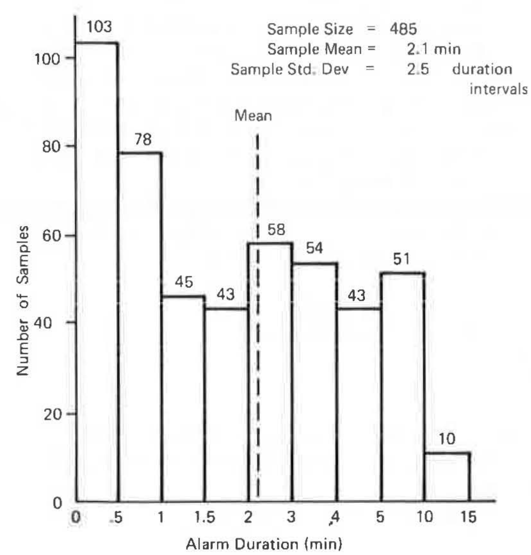


Figure 3. False-alarm duration histogram.



$$LR(X' = 1) = P(2|X)/(1|X) = 60.4 >> 1 \tag{3}$$

The likelihood ratios were calculated for two other values of X' and are shown plotted in Figure 4. Clearly, X' = 1 min is the best choice.

Experimental Results

According to the preceding analysis of the QEW historical data, it appears that a computer algorithm with a 1-min incident-duration persistence test can effectively remove 37.3 percent of the false alarms without excessively delaying the incident-detection response time. This can be accomplished by simply delaying the incident alarm output for a 1-min period. At the end of the minute, if the incident alarm still persists, then the pending-incident alarm can be issued by the incident-detection program. Otherwise, the pending-incident alarm will be cancelled.

This incident-duration persistence check algorithm was implemented on the QEW FSCS in March 1978, and the algorithm performance data were collected from March to June 1978. During this period, the false-alarm rate was reduced by 33 percent from the previous value of 0.09 to 0.06 percent. This was achieved at the expense of a reduction in detection rate of from 85 to 74 percent.

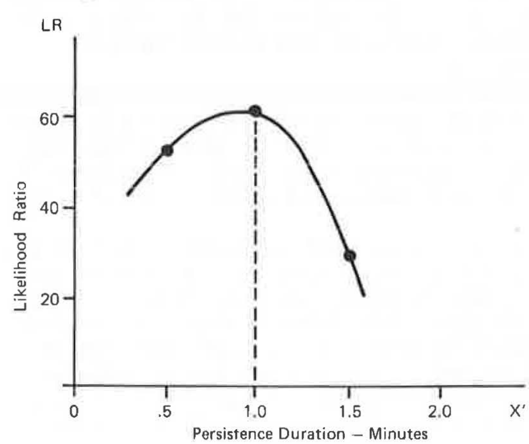
To put the significance of this improvement in better perspective, one might translate this 33 percent reduction in false-alarm rate into the elimination of 160 false alarms if this algorithm had been applied from January 1977 to February 1978. The reduction in detection rate can only mean that those incidents that have an alarm duration less than or equal to 1 min are not being detected.

Normally these short-duration incidents appear to have only minor, transient effects on the traffic flow. Their not being detected presents no operational problem. Also, the accompanying increase in the detection time of 1 min has negligible effect on the incident-management operation. These are confirmed by a lack of complaints from QEW FSCS operators.

LANE INCIDENT DETECTION ON A MULTILANE FREEWAY

The development and experimental verification of the lane incident-detection system described here was based on

Figure 4. Variation of likelihood ratio with persistence duration.



1. Consideration of only a three-lane freeway,
2. Investigation of only single-lane freeway incidents,
3. Detectorization of all three lanes at each incident detector station, and
4. Identification of the lane incident location after identification of the station incident location.

In this section, the committee-machine concept (4) is first applied to the general problem of multilane incident detection. This is followed by the description of a realistic (though simplified) practical application and some experimental results.

Committee-Machine Approach

Freeway-lane incident detection can be considered a pattern-recognition process with three pattern categories, each corresponding to the occurrence of an incident in one of the three freeway lanes (see Figure 5). Figure 5 also shows QEW FSCS detector system configuration. With this type of configuration, a 30-s lane occupancy, lane speed, and lane volume data set can be obtained. The data set containing the patterns to be so classified is the selected lane-surveillance data from the various freeway detector stations. These patterns are processed by the various lane incident-detection algorithms to produce an incident-lane number decision. The lane with the highest number of decisions in its favor is then selected as the most probable incident-lane location based on the majority decision principle.

To illustrate how the above concepts can be formulated into a committee-machine structure, consider first the basic committee logic decision unit (CLDU) shown in Figure 6. This unit is provided with surveillance data from both upstream and downstream detector stations for all three lanes as its input and contains an algorithm that generates a decision about which of the three lanes has experienced the incident. These units are arranged in banks to form the first layer of a committee-machine structure, as illustrated in Figure 7. The second layer of the committee machine is a vote-taking logic unit (VTLU) that accepts the decision outputs from the first-layer CLDUs and selects the lane where the incident occurred according to the majority decision principle. The three such two-layered committee machines shown in Figure 7 correspond to the case where occupancy, volume, and speed surveillance data are all available. The outputs of these three two-layered committee machines are fed to the third-layer VTLU, possibly with different weights, which will then select an incident lane according to the majority decision principle.

The VTLU polls the decision outputs from each of the CLDUs in the first layer (or the weighted counts from the three VTLUs in the second layer), summarizes the total number of decision counts for each type of decision output, and selects a desired decision output according to the consensus function $\max [n_i/N]$, where n_i is a number of decision counts for decision category i for i = 1, 2, 3, and N is the total number of algorithms (and therefore, CLDUs) dedicated to generating decisions for any given VTLU. In other words, the decision type i that has the maximum number of decision counts is designated as the lane where the incident occurred.

Figure 5. Lane incident detection on a three-lane freeway.

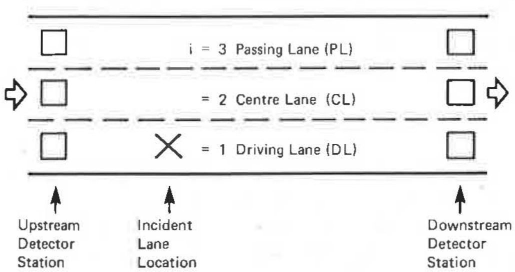


Figure 6. Committee logic decision unit.

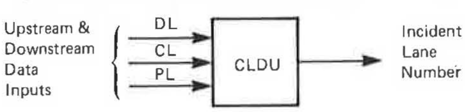
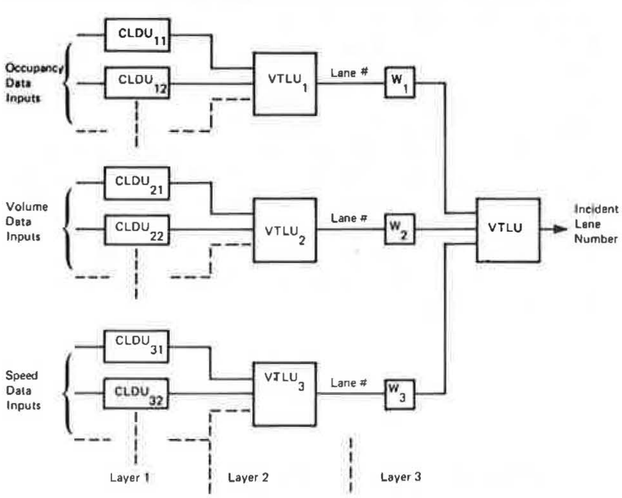


Figure 7. Three-layer committee machine for lane incident detection.



Practical Application and Experimental Results

To illustrate the practical application of the committee-machine approach, the two-layer committee-machine structure shown in Figure 8 was employed. All of the CLDUs were identical in function but, in effect, used a different algorithm because each was provided with a different time slice (30-s sample time) of lane-occupancy data. Each CLDU computed the differential occupancy,

Figure 8. Two-layer committee-machine structure.

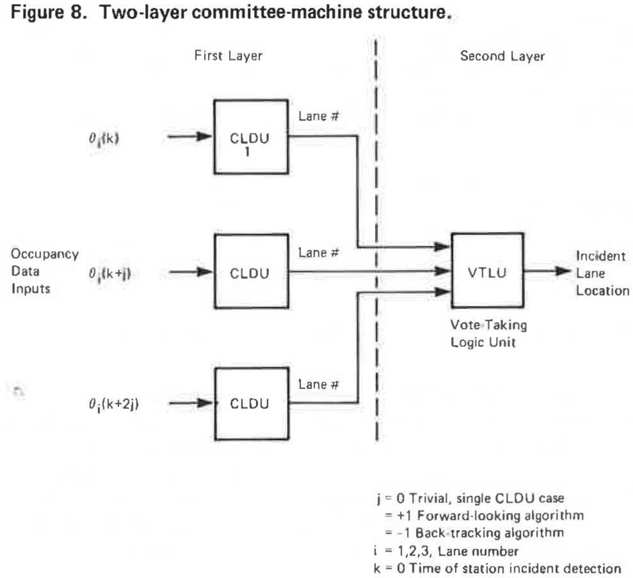


Table 1. Percentages of lane occupancy for center-lane incident.

Time	Upstream-Station Data by Lane			Downstream-Station Data by Lane		
	Driving	Center	Passing	Driving	Center	Passing
7:52:30	30	36	53	61	53	62
7:53:00	62	53	53	55	44	44
7:53:30	51	40	36	37	41	36
7:54:00	38	72	45	42	29	34
7:54:30	25	100	47	16	14	19
7:55:00	35	49	46	8	13	12
7:55:30	42	80	71	17	14	12
7:56:00	36	40	50	10	17	12
7:56:30	27	43	61	6	11	15

$\sigma_i(k)$, from downstream-station lane-occupancy data according to the following equation:

$$\sigma_i(k) = \{[\theta_i(k)]_i - \theta_i(k)\}/[\theta_i(k)]_i \qquad (4)$$

where

$[\theta_i(k)]_i$ = downstream-station occupancy at time slice k averaged over all three lanes,
$\theta_i(k)$ = downstream-station lane occupancy at time slice k for i = 1, 2, 3, and
k = 30-s time slice.

The minimum of $\sigma_i(k)$ was then selected and compared to an empirically determined constant k. If min $[\sigma_i(k)] \geq$ K (K = 0.2 for the QEW freeway section being considered), then the CLDU indicated lane i as the incident location. Otherwise, the CLDU sought the maximum upstream-station lane occupancy and indicated lane i as the incident location.

As indicated in Figure 8, three different types of algorithms were tested. The first (j = 0) is a trivial case where only data at the time of station incident detection (k = 0) were used; in this case two of the three CLDUs are redundant. In the second case (j = +1) forward-looking algorithms were used in which data at the time of station incident detection and those from the two succeeding time slices were used. The third case (j = -1) employed back-tracking algorithms in which data at the time of station incident detection and those from the preceding two time slices were used.

The rationale for testing the forward-looking and back-tracking types of algorithms is based on the observed highly stochastic nature of the lane incident data. This is clearly illustrated by Table 1, which shows typical upstream and downstream lane-occupancy data for several time slices both before and after the time of station incident detection.

The experimental results obtained by testing the above-defined algorithms in the two-layer committee-machine configuration shown in Figure 8 are summarized below

Algorithm Type	Detection Rate (%)	Detection Time
Trivial single-CLDU case	67.8	Same as for station incident detection
Forward-looking	67.8	Two time slices (1 min) after station incident detection
Back-tracking	85.7	Same as for station incident detection

They are based on the same 28 samples of lane incident data from the QEW FSCS. The back-tracking algorithms achieved an 85.7 percent lane incident-detection rate, which is clearly superior to the other two algorithms, which achieved a rate of only 67.8 percent. The back-tracking algorithms also have the obvious advantage of shorter lane incident-detection times compared to the other two.

SUMMARY AND CONCLUSIONS

1. A pattern-recognition approach was successfully applied to the development of improved incident-detection algorithms. The results indicate that this approach provides a useful conceptual framework and is a practical tool for examining such problems as well.
2. The true- and false-incident-alarm identification process was considered as a pattern-recognition process and the maximum-likelihood decision principle was applied to develop an optimum incident-duration persistence test. This was tested experimentally and was found to reduce the false-alarm rate from 0.09 to 0.06 percent during a three-month field test.
3. A multilayered committee-machine structure was developed to implement a set of freeway-lane incident-detection algorithms. This concept was tested experimentally by using a two-layer committee-machine structure that achieved a lane-detection rate of 85.7 percent based on 28 samples of historical freeway-lane incident data.

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