Fast Automatic Incident Detection on Urban and Rural Freeways Using Wavelet Energy Algorithm

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Abstract: A comprehensive evaluation is presented of the single-station wavelet energy neural network freeway incident-detection algorithm of Karim and Adeli. Quantitative performance measures of detection rate, false alarm rate, and detection time as well as the qualitative measure of portability are investigated for both urban and rural freeway conditions. Further, the performance of the algorithm is compared with that of California algorithm 8. This research demonstrates the portability of the wavelet energy algorithm and its excellent performance for urban freeways across a wide range of traffic flow and roadway geometry conditions, regardless of the density of the loop detectors. Rural freeways present additional challenges in that flow rates are low and detector stations are spaced further apart. Considering the difficulty in automatic detection of incidents on rural freeways, the new wavelet energy algorithm performs well on such freeways. The algorithm is fast as it detects an incident on urban freeways in less than 2 min and on rural freeways in less than 3 min.

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Introduction

There are two major uses of automatic incident detection in an advanced traffic management system (ATMS). The first is to signal the dispatch of emergency crews to the site for prompt medical support, obstruction removal, and general maintenance of motorists' safety, and the second is to provide useful information to the routing control system to maintain and optimize systemwide performance. For the best performance, the incident detection system must provide quick and reliable information.

The traffic incident detection system is a main component of an ATMS (Fig. 1). The other components that make up the ATMS include the traffic routing and control system, the data archiving system, and the pre- and postprocessing systems. Traffic sensors provide the main source of data for analysis. Additionally, information may be obtained from the news media, special traffic probe vehicles, and motorists' call-ins. Traffic control devices such as entry ramp access control and changeable message signs use the real-time information on traffic conditions to guide and control traffic throughout the network.

Recently, Adeli and Karim (2000) presented a new multiparadigm intelligent system approach to the solution of the freeway incident detection problem employing advanced signal processing, neural network pattern recognition (Adeli and Hung 1995; Adeli and Park 1998), and classification techniques. This is a single-station algorithm that uses loop detector data upstream of the incident. A wavelet-based denoising technique is employed to eliminate undesirable fluctuations in observed data from traffic sensors (Samant and Adeli 2000). Fuzzy *c*-mean clustering is used to extract significant information from the observed data and to reduce its dimensionality.

A radial basis function neural network (RBFNN) is developed to classify the denoised and clustered observed data. The performance of the model is evaluated and compared with the benchmark California algorithm 8 using both real and simulated data (Karim and Adeli 2002a). The new algorithm outperformed the California algorithm consistently under various scenarios. The false alarm rate ranges from 0 to 0.07% for the new algorithm and 0.5 to 3.8% for the California algorithm. The incident detection time ranged from 64 s for larger flow rates and shorter distances to the detector station to 480 s for lower flow rates and longer distances to the detector station.

In order to reduce the incident detection time to the range of 1 to 2 min on urban freeways, Karim and Adeli (2002b) developed a new single-station pattern recognition algorithm for freeway incident detection using data obtained from loop detectors downstream of the incident. The algorithm uses an innovative energy representation of the traffic data in the wavelet domain to denoise and enhance desirable features before classifying them by a radial-basis-function neural network. The algorithm is based on a new methodology for the development of freeway incident detection algorithms that emphasizes denoising, feature enhancement, and the selection of a traffic pattern independent of roadway geometry and traffic flow conditions.

The purpose of evaluating a new freeway incident detection algorithm is to determine its robustness under different traffic flow and roadway geometry conditions and thus to assess its cost-effectiveness for practical networkwide implementation. Three quantitative performance measures are commonly used for this purpose: the detection rate (percentage of the number of correctly detected incidents out of the total number of incidents in the data set); the false alarm rate (percentage of the number of false alarms signaled by the algorithm out of the total number of decisions

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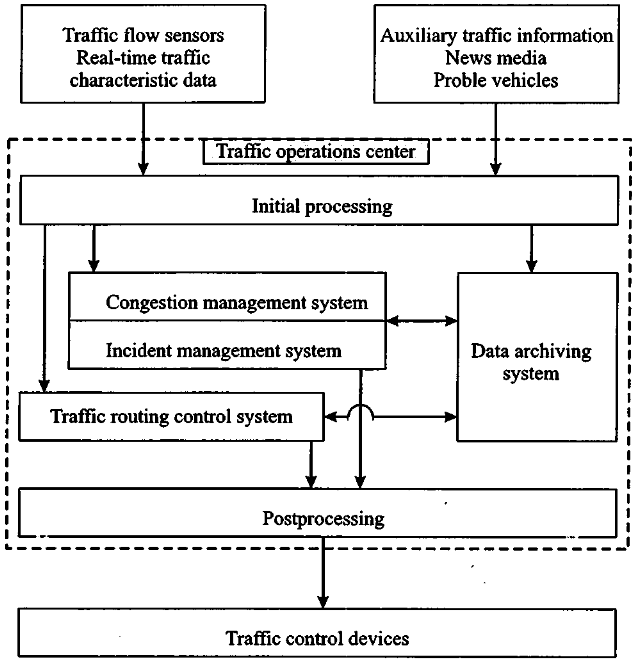

Fig. 1. Information processing in advanced traffic management system

made), and the detection time (the time it takes for the algorithm to signal the incident after its occurrence).

These three quantitative measures, however, do not provide a complete picture of an algorithm's performance in practice. The qualitative measure of portability without recalibration must also be considered in conjunction with the quantitative measures. This is because the cost of maintaining and recalibrating the algorithm to perform acceptably at all locations in a large freeway system can make its networkwide implementation economically infeasible. There is a cost associated with every missed detection and every false alarm, the time taken to detect an incident, and the efforts exerted to maintain and calibrate the algorithm. These costs ultimately determine the success or failure of the algorithm in practice. As reported by Abdulhai and Ritchie (1999), traffic control centers place differing cost premiums on each performance measure whenever a trade-off is sought. In any case, a higher detection rate, lower false alarm rate, and shorter detection time are always desirable. Moreover, an algorithm that is readily portable is often preferred to one that performs excellently only at a given location.

All freeway incident detection algorithms reported in the literature have been developed and evaluated for urban freeway systems. This is understandable because of the negative impacts that incidents create on congested urban freeways and the need to remove them as soon as possible. However, there is also a need to develop and evaluate incident detection algorithms for rural freeways. The number of vehicle-miles of rural freeways in the United States is much larger than that for urban freeways, and there is indeed a need for automatic and rapid detection of incidents so that emergency/medical support can be dispatched in time. Challenges such as low flow rates and long distances between loop detectors have hampered the development of algorithms that work effectively in rural freeway environments.

This article first presents a comprehensive parametric evaluation of the new wavelet energy freeway incident detection algorithm of Karim and Adeli (2002b) using both real and simulated data. Several urban freeway scenarios are simulated for evaluation by varying the flow rate, the number of lanes, and the distance of the incident from detector station. The effects of on- and off-ramps are also considered. Next, the algorithm is evaluated on rural freeway scenarios where flow rates are low and detector stations are spaced far apart. For comparison, the performance of California algorithm 8 is also presented.

The following section delineates factors to consider in rural freeway incident detection. Then the wavelet energy freeway incident detection algorithm is described step by step, followed by a comprehensive evaluation of the algorithm and discussions of the test results.

Factors to Consider in Rural Freeway Incident Detection

Traffic on urban freeways is characterized by high demand and periodic congestion that reduce the level of service expected by motorists. Because of the high demand and insufficient capacity, the level of service degrades dramatically when an obstructing incident occurs. Therefore, quick and reliable identification and localization of such incidents is essential to prevent unacceptable backups and delays caused by obstructions that are not cleared quickly. As such, an effective incident detection algorithm must be both reliable and fast in detecting an incident.

Traffic on rural freeways, on the other hand, is usually congestion-free under normal operating conditions. Furthermore, the impact of an obstructing incident is often less severe because traffic demands on rural freeways usually do not exceed capacity. Nevertheless, the need still exists for reliable automatic incident detection. Incidents in rural areas, unlike those in urban areas, may go unreported for several minutes. Furthermore, the transit of emergency and medical support to rural locations can take more time. Therefore, rapid automatic notification of an incident condition is very valuable. Automatic incident detection on rural freeways is challenging because of low flow rates and large distances between detectors. Most of the incident detection algorithms developed so far have not been evaluated under such conditions and in general perform poorly under low flow-rate conditions.

Several factors have to be considered in the development and evaluation of an automatic rural freeway incident detection algorithm. These considerations are in general more stringent and demanding than those required for reliable detection on urban freeways.

- Density of detectors: It is practically infeasible to have closely spaced loop detectors on rural freeway segments. Thus, the algorithm must work reliably under situations where detectors are spaced 2 to 3 km apart. The cost-effectiveness of the solution improves dramatically with an increase in the distance between detectors at which the algorithm can produce reliable results.
- Detection time: The detection time on rural freeways is important, not for traffic management purposes, but for emergency medical support reasons. Often a serious congestion may not develop as a result of a rural incident. However, rapid identification and localization of the incident are still necessary to ensure that emergency support can arrive on the scene at the earliest possible time. There is a trade-off between detection time and the distance between detectors. In general, the closer the spacing between detectors, the shorter the detection time; however, reducing the spacing between detectors significantly increases the number of detectors that have to be installed and maintained on long stretches of rural freeways.

- Low prevailing flow rates: Traffic incident detection algorithms normally depend on the change in traffic pattern that results from an incident to identify its occurrence. However, when the prevailing flow rate is low and the incident does not reduce freeway capacity significantly, the change in traffic pattern can be minor. This poses a serious challenge in the design of reliable algorithms.
- Calibration and maintenance: Because of the huge mileage of rural freeways, calibration and maintenance of algorithms at all locations can become extremely costly. Therefore, algorithms for rural freeway incident detection should require minimal maintenance for acceptable operational performance. Custom calibration of the algorithm at each location is practically infeasible.

An algorithm that is cost-effective for implementation on an urban freeway system may be impractical for implementation on rural freeways. In general, a lower performance should be expected for an algorithm on rural freeways than on urban freeways because of the constraints on detector spacing and flow rates. The goal is to have an algorithm that requires no recalibration with acceptable performance. Note that these considerations apply to passive techniques for incident detection only where traffic data obtained from loop detectors embedded in the pavement are analyzed to identify characterizing patterns. Active techniques such as in-vehicle transponders may be more effective in rural settings but require more investment and are often perceived as intrusive by the public.

Wavelet Energy Model for Freeway Incident Detection

The new single-station incident detection algorithm developed by Karim and Adeli (2002b) takes as inputs a time series of lane occupancy and lane speed at the upstream detector station or a time series of lane occupancy and lane flow rate at the downstream detector station. Each time series consists of 16 data values averaged over and obtained at every 20 or 30 s interval. The patterns at both upstream and downstream detector stations are transformed and represented in the wavelet domain as an energy functional. This representation makes it possible to denoise, enhance, and reduce the dimensionality of the patterns effectively and efficiently. The processed patterns are then classified into one of two states representing either an incident or incident-free condition by a radial basis function neural network. The key ideas and detailed algorithm are described in Karim and Adeli (2002b). A complete step-by-step algorithm is presented in this section.

Only the downstream station logic is implemented and tested in this evaluation. It was found that the upstream logic produced results almost identical—and in the case of detection time, slightly inferior—to those produced by the downstream logic. Therefore, the wavelet energy algorithm consists of the collection, processing, and classification of the downstream lane occupancy and flow-rate time-series data. In a freeway management system, this algorithm is implemented at every detector station and reports on the presence or absence of an incident upstream of the station. The algorithm is shown schematically in Fig. 2 and described in the following steps.

1. Obtain the last 16 lane occupancy and lane flow rate readings and form the sequences $f_O[i]$ and $f_F[i]$, respectively, where $i=1,\ldots,16$. When readings are available every 20 s, for example, this process is performed every 20 s by adding the new reading and dropping the last reading in the sequence.

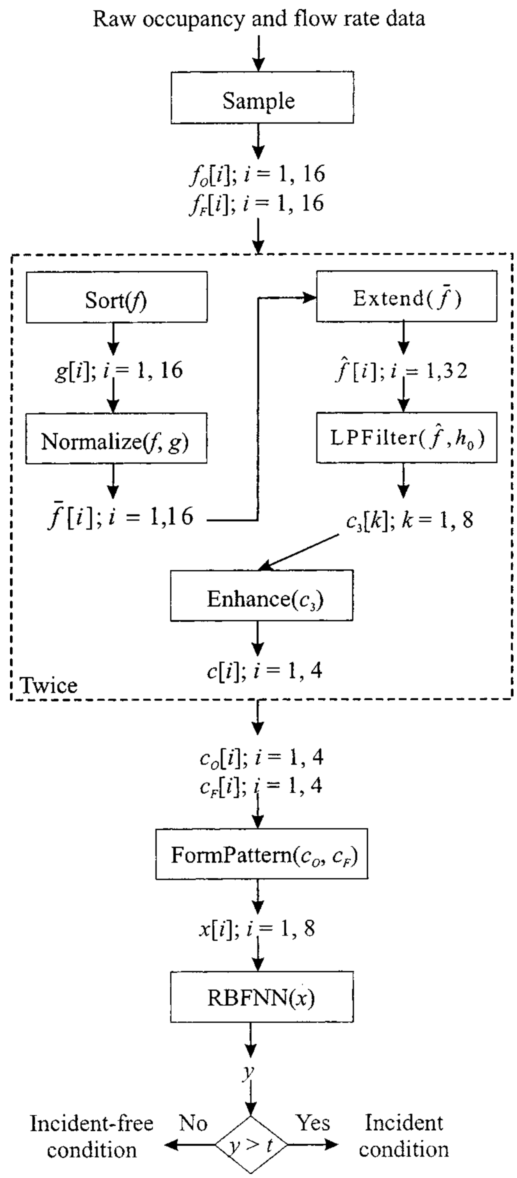

Fig. 2. Wavelet energy freeway incident detection algorithm

2. For each data sequence $f[i]$ perform the following computations:

   a. Sort the elements in the sequence $f[i]$ to create a new sequence $g[i]$ such that

   $$g[i] \geqslant g[i+1]; \quad i=1,\ldots,15;$$

   b. Normalize $f[i]$ by dividing all its elements by the average of the two largest values:

   $$\bar{f}[i]=\frac{f[i]}{0.5(g[1]+g[2])}; \quad i=1,\ldots,16 \tag{1}$$

   c. Extend the normalized sequence $\bar{f}[i]$ by eight elements on each side as follows:

   $$\hat{f}[i]=\begin{cases} 0.5(\bar{f}[1]+\bar{f}[2]); & 1\leqslant i\leqslant 8 \\ \bar{f}[i-8]; & 9\leqslant i\leqslant 24 \\ 0.5(\bar{f}[15]+\bar{f}[16]); & 25\leqslant i\leqslant 32 \end{cases} \tag{2}$$

   The sequence $\hat{f}[i]$ now has 32 elements. The sequences are extended to avoid wavelet transform end effects from distorting the shape of the traffic pattern (Karim and Adeli 2002b).

d. Perform a two-stage, low-pass filter of the sequence $\hat{f}[i]$ as follows:

$$c_4[k]=\sum_i h_0[i-2k]\hat{f}[i] \qquad (3)$$

$$c_3[k]=\sum_i h_0[i-2k]c_4[i] \qquad (4)$$

where $h_0[i]=8$-coefficient low-pass filter for the Daubechies (Daubechies 1992) wavelet system of length 8. The sequence $c_3[i]$ $(i=1,\ldots,8)$, called the scaling coefficients, represents a lower scale or resolution (scale 3) of the original 32 element sequence $\hat{f}[i]$ (scale 5).

e. Enhance the sequence $c[i]$:

$$c[i-2]=|c_3[i]|^2; \quad i=3,4,5,6 \qquad (5)$$

The sequence $c[i]$ has 4 elements representing the squared scaling coefficients (a measure of energy in the wavelet domain) for the middle 16 elements of $\hat{f}[i]$. These elements correspond to the input traffic data before it is extended for processing. Let the processed lane occupancy and flow rate data be denoted as $c_O[i]$ and $c_F[i]$, respectively.

3. Form the feature pattern by concatenating the processed lane occupancy and flow rate sequences:

$$x[i]=c_0[i],\ x[i+4]=c_F[i]; \quad i=1,\ldots,4 \qquad (6)$$

The 8-element sequence $x[i]$ represents the denoised, clustered, and enhanced pattern that is used in the subsequent step for classification.

4. Feed forward the feature pattern $x[i]$ through a trained RBFNN. The neural network has 8 input nodes, 12 hidden nodes with Gaussian transfer functions, and 1 output node with a linear transfer function. If the output is greater than a preselected threshold (a small positive value such as 0.2), then an incident is signaled; otherwise, the pattern represents an incident-free condition.

The RBFNN is trained with incident and incident-free patterns to determine the weights of the links connecting the input layer to the hidden layer and the links connecting the hidden layer to the output node. Training is done iteratively to minimize the output error. Once the network is trained, no further training is necessary. For further details, refer to Karim and Adeli (2002b).

Evaluation and Parametric Investigation

Goals

A comprehensive evaluation of the wavelet energy freeway-incident detection algorithm is presented in this section. The goals of the evaluation are to (1) determine the quantitative performance measures (detection rate, false alarm rate, and detection time) for typical urban freeway conditions; (2) determine the quantitative performance measures for typical rural freeway conditions; (3) assess the transferability or portability of the algorithm—that is, compare the algorithm's performance under different roadway geometry and traffic flow conditions without recalibration; (4) perform a parametric evaluation of the algorithm—that is, determine the sensitivity of the algorithm to variations in roadway geometry and traffic flow conditions; and (5) compare the performance of the algorithm with that of California algorithm 8 (Payne and Tignor 1978).

The roadway geometry conditions evaluated are the number of lanes (two, three, and four); the distance of the incident from the detector station (152 to 2,744 m); and the proximity to on- and off-ramps. Traffic flow is varied from 500 to 2,000 vehicles per hour (vph) per lane. An incident is modeled as the blockage of one lane and the 50 or 40% reduction in capacity of the adjacent lane(s). The time of blockage is varied from 3 to 10 min.

Data

The majority of the traffic data used in the evaluation are generated using the simulation software TSIS (http://www.fhwa-tsis.com/). TSIS is a microscopic simulation tool that considers each vehicle as a separate entity in a stochastic model of vehicles and their environment (roadway geometry, pavement conditions, proximity to other vehicles, and so on).

In addition to simulated data, real data from the San Francisco Bay area freeway service patrol project's I-880 database are also used for evaluation. This database is a collection of binary files of loop detector outputs collected over a period of about two months. A software program is used to process this database and extract selected information in a readable format for further processing. The database contains basic information such as lane occupancy, flow rate, and speed. The information on the location and time of incidents is recorded by human observers and has to be correlated to the loop data for analysis. Because this information is recorded by humans, it is not reliable and has to be verified by visual observation of the loop detector data. For detection rate testing, data for 21 single-lane blocking incidents are extracted from the database. These incidents occurred during the time period 7 a.m. to 6 p.m. on weekdays. For false alarm testing, 4 h of incident-free data are extracted from weekday morning rush hour traffic (7 a.m. to 11 a.m.). These time periods include congested traffic conditions on the I-880 freeway.

Training and Calibration

The wavelet energy freeway-incident detection algorithm is trained with 60 incident and 60 incident-free patterns that are chosen randomly from all the simulated data generated for the evaluation. No real data are used in the training phase of the network. The training determines the weights for the RBFNN. Once the algorithm is trained, no further training is done as it is evaluated using different sets of data.

California algorithm (Payne and Tignor 1978) is a well-known two-station comparative algorithm for freeway incident detection that uses lane occupancy data as input. The algorithm logic consists of a sequence of decisions where occupancy-based input values are compared with preselected thresholds to characterize traffic flow into one of five major states. California algorithm 8 is one of several variations developed in the 1970s. It incorporates an incident persistence test and a compression wave suppression test to reduce the generation of false alarms.

Six parameters or thresholds have to be calibrated for the algorithm. Employing the same 60 incident and 60 incident-free patterns used for the wavelet energy algorithm, calibration of the California algorithm is done in a trial-and-error fashion until the misclassification error is minimized. The threshold values used in this evaluation are as follows (these values produced the best overall calibration results for the data used):

- Threshold of occupancy difference between consecutive stations = 13%;
- Threshold of percent occupancy change at downstream station over the time interval = 30;
- Threshold of percent occupancy difference between consecutive stations = 30;
- Threshold of occupancy at downstream station = 15%;

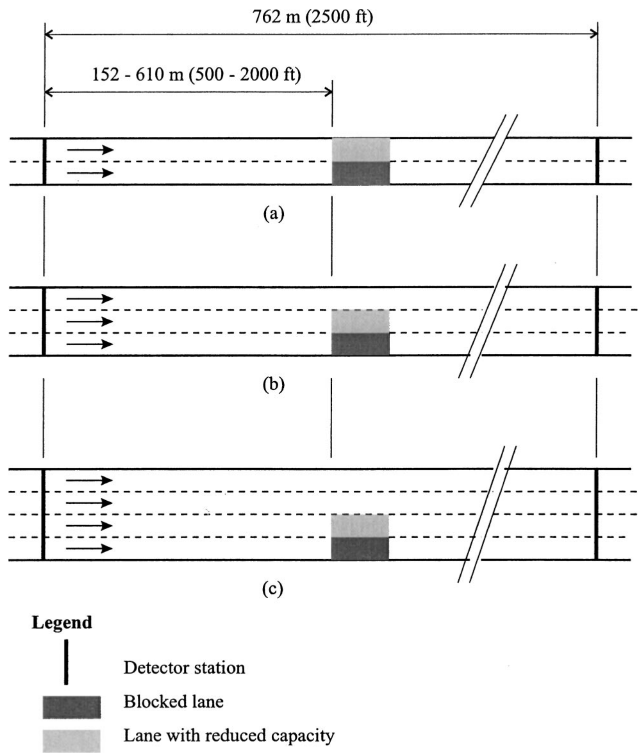

Fig. 3. Layout of urban freeway segments simulated for parametric evaluation

- Second threshold of occupancy at downstream station=30%; and
- Number of compression wave suppression periods=2.

The same set of parameters is used throughout the evaluation without recalibration. This is done to test the portability property of the algorithm and compare it with that of the new wavelet energy algorithm.

Parametric Evaluation Using Simulated Data on Typical Urban Freeways

Fig. 3 shows the freeway layouts simulated for the parametric evaluation. These layouts represent typical urban freeway segments with two, three, and four lanes with detectors spaced 762 m apart. The location of the incident, which consists of the blockage of one lane and the 50% reduction in capacity of the adjacent lane, is varied from 152 to 610 m from the downstream (or upstream) detector station. The flow rates considered are 1,000, 1,500, and 2,000 vph per lane.

The performance of the new wavelet energy algorithm is compared with that of California algorithm 8 on two-, three-, and four-lane freeways in Tables 1, 2, and 3, respectively. The wavelet energy algorithm performs perfectly in all scenarios in terms of producing an overall detection rate of 100% and a false alarm rate of zero. The California algorithm, on the other hand, failed to detect 25% of the incidents on three- and four-lane freeways. This result demonstrates the excellent performance of the new wavelet energy algorithm in difficult-to-detect situations such as the closure of just one lane on a multiple-lane freeway when the prevailing flow rate is low. In general, whenever the prevailing flow rate is less than the reduced capacity after the incident, incident detection algorithms such as California algorithm 8 are less likely to detect an incident because a significant queue does not develop in a short period of time (say, a few minutes). This characteristic also exists in other incident detection algorithms that utilize only the upstream occupancy to detect the presence of an incident condition.

The detection times reported by the new wavelet energy algorithm varied from 56 to 116 s. Detection time generally increases with an increase in the distance of the incident from the downstream detector station; however, this variation of detection time with location of incident is substantially less pronounced than that for the California algorithm. This is evident from Fig. 4, which compares the detection times for the wavelet energy and California algorithms on a two-lane freeway. The detection time for the California algorithm is a lot longer, varying from 76 to 480 s, and increases substantially with a decrease in flow rate and distance of incident from the downstream detector station. This is because the California algorithm is based on the formation of congestion on the upstream side of the incident, which takes more time to develop when the prevailing flow rate is low. The wavelet energy algorithm, on the other hand, does not exhibit this behavior, as seen in Fig. 4. The performance of the wavelet energy algorithm is also not greatly affected by changes in geometry such as the number of lanes, as noted in Fig. 5. The relative independence of the wavelet energy algorithm from changes in flow rate and road-

Table 1. Performance of New Wavelet Energy Algorithm and California Algorithm 8 on Two-Lane Freeway

		Wavelet Energy Algorithm			California Algorithm 8		
Flow rate (vph per lane)	Location (m)[a]	Detections	False alarms	Detection time (s)	Detections	False alarms	Detection time (s)
1,000	152	5/5	0/150	80	5/5	0/150	480
	305	5/5	0/150	96	5/5	0/150	384
	457	5/5	0/150	68	5/5	0/150	252
	610	5/5	0/150	112	5/5	0/150	164
1,500	152	5/5	0/150	68	5/5	1/150	228
	305	5/5	0/150	80	5/5	0/150	176
	457	5/5	0/150	92	5/5	0/150	132
	610	5/5	0/150	96	5/5	0/150	92
2,000	152	5/5	0/150	68	5/5	0/150	132
	305	5/5	0/150	92	5/5	1/150	116
	457	5/5	0/150	92	5/5	2/150	84
	610	5/5	0/150	124	5/5	0/150	96
Totals		60/60 (100%)	0/1,800 (0%)		60/60 (100%)	4/1,800 (0.22%)	

[a]Location of incident from downstream detector station. Distance between detector stations is 762 m.

Table 2. Performance of New Wavelet Energy Algorithm and California Algorithm 8 on Three-Lane Freeway

		Wavelet Energy Algorithm			California Algorithm 8		
Flow rate (vph per lane)	Location (m)[a]	Detections	False alarms	Detection time (s)	Detections	False alarms	Detection time (s)
1,000	152	5/5	0/150	56	0/5	0/150	—
	305	5/5	0/150	68	0/5	0/150	—
	457	5/5	0/150	80	0/5	0/150	—
	610	5/5	0/150	72	5/5	0/150	248
1,500	152	5/5	0/150	56	5/5	0/150	264
	305	5/5	0/150	76	5/5	0/150	208
	457	5/5	0/150	76	5/5	1/150	132
	610	5/5	0/150	88	5/5	0/150	96
2,000	152	5/5	0/150	88	5/5	0/150	148
	305	5/5	0/150	116	5/5	0/150	136
	457	5/5	0/150	100	5/5	0/150	92
	610	5/5	0/150	96	5/5	1/150	76
Totals		60/60 (100%)	0/1,800 (0%)		45/60 (75%)	2/1,800 (0.11%)	

[a]Location of incident from downstream detector station. Distance between detector stations is 762 m.

way geometry demonstrates its superior portability property as compared to the California algorithm.

False alarms generated by automatic freeway-incident detection algorithms are often a major source of excessive operational costs. Traffic control centers would often prefer an algorithm that generates fewer false alarms over another one with a better detection rate but a higher false alarm rate. On urban freeway segments, the wavelet energy algorithm generated no false alarms, thus producing an overall false alarm rate of zero. In contrast, the California algorithm produced false alarm rates of 0.22, 0.11, and 0.28% on two-, three-, and four-lane freeways, respectively. These false alarms are generated during moderate and heavy traffic flow conditions.

False Alarm Performance in Vicinity of On- and Off-Ramps

Traffic flow in the vicinity of on- and off-ramps is often chaotic and marked by large fluctuations in occupancy, speed, and flow rate as vehicles maneuver to enter and exit the freeway. This is especially true for urban freeways, where ramps are usually closely spaced and the entering and exiting flow rates are high. On- and off-ramps are thus geometric bottlenecks that create nonhomogeneities in traffic flow and are responsible for generating a large number of false alarms from existing automatic freeway incident detection algorithms. To test the false alarm performance of the algorithms in such situations, a three-lane urban freeway segment with two on- and off-ramps is modeled for simulation (Fig. 6). For this freeway geometry four traffic-flow scenarios are evaluated, as described in Table 4. Each scenario consists of three time periods of different mainline and on- and off-ramp traffic flow rates. This is done to simulate sudden changes in entering and exiting flows on heavy traffic freeways that often cause automatic freeway-incident detection algorithms to produce false alarms.

The false alarm performance of the wavelet energy algorithm and California algorithm 8 in the vicinity of on- and off-ramps is given in Table 5. The remarkable false alarm performance of the wavelet energy algorithm is evident; it produced no false alarms at any of the six detector station locations and in 27,000 ($4\times6\times1{,}125$) decisions. The California algorithm, on the other hand, produced numerous false alarms, ranging from 0.5 to 3.8%, especially for the roadway segment between detectors 4 and 5 (Fig. 6).

Note that neither algorithm is recalibrated or retrained for this and any other evaluation. This is done to ascertain the portability property of the algorithms. California algorithm 8 may be recalibrated for each segment to produce fewer false alarms. However,

Table 3. Performance of New Wavelet Energy Algorithm and California Algorithm 8 on Four-Lane Freeway

		Wavelet Energy Algorithm			California Algorithm 8		
Flow rate (vph per lane)	Location (m)[a]	Detections	False alarms	Detection time (s)	Detections	False alarms	Detection time (s)
1,000	152	5/5	0/150	60	0/5	0/150	—
	305	5/5	0/150	68	0/5	0/150	—
	457	5/5	0/150	72	2/5	0/150	440
	610	5/5	0/150	84	5/5	0/150	168
1,500	152	5/5	0/150	72	5/5	0/150	268
	305	5/5	0/150	96	5/5	0/150	188
	457	5/5	0/150	92	5/5	1/150	132
	610	5/5	0/150	84	5/5	0/150	96
2,000	152	5/5	0/150	68	5/5	1/150	140
	305	5/5	0/150	84	5/5	1/150	128
	457	5/5	0/150	84	5/5	2/150	96
	610	5/5	0/150	108	5/5	0/150	84
Totals		60/60 (100%)	0/1,800 (0%)		47/60 (78.3%)	5/1,800 (0.28%)	

[a]Location of incident from downstream detector station. Distance between detector stations is 762 m.

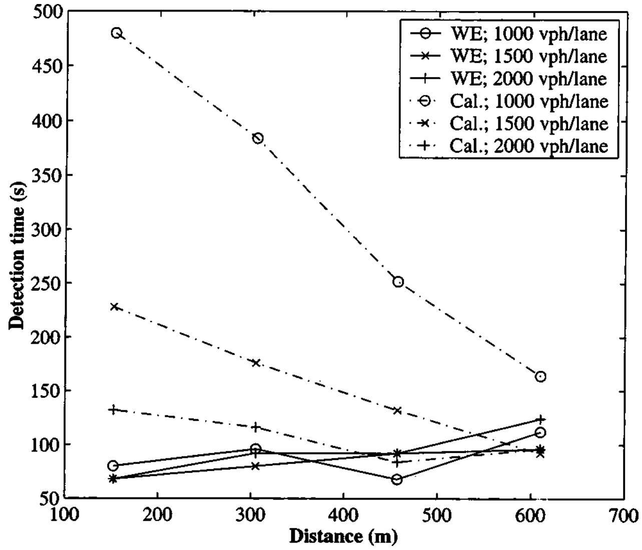

Fig. 4. Variation of detection time with distance of incident from downstream detector station on two-lane urban freeway for wavelet energy algorithm (WE) and California algorithm 8 (Cal)

this procedure is time-consuming and expensive on a large urban freeway management system. Furthermore, this procedure may be required on a regular basis to ensure optimal performance with changing traffic-flow conditions. The wavelet energy algorithm, on the other hand, performed excellently without any need for retraining and thus is readily transferable and portable for implementation on urban freeway systems.

Evaluation on Rural Freeways

Rural freeways present a challenge for passive automatic freeway incident detection algorithms that use loop detector data. As discussed earlier, it is economically infeasible to have closely spaced loop detectors on the large network of rural freeways in the United States. Thus, incident detection algorithms can only rely

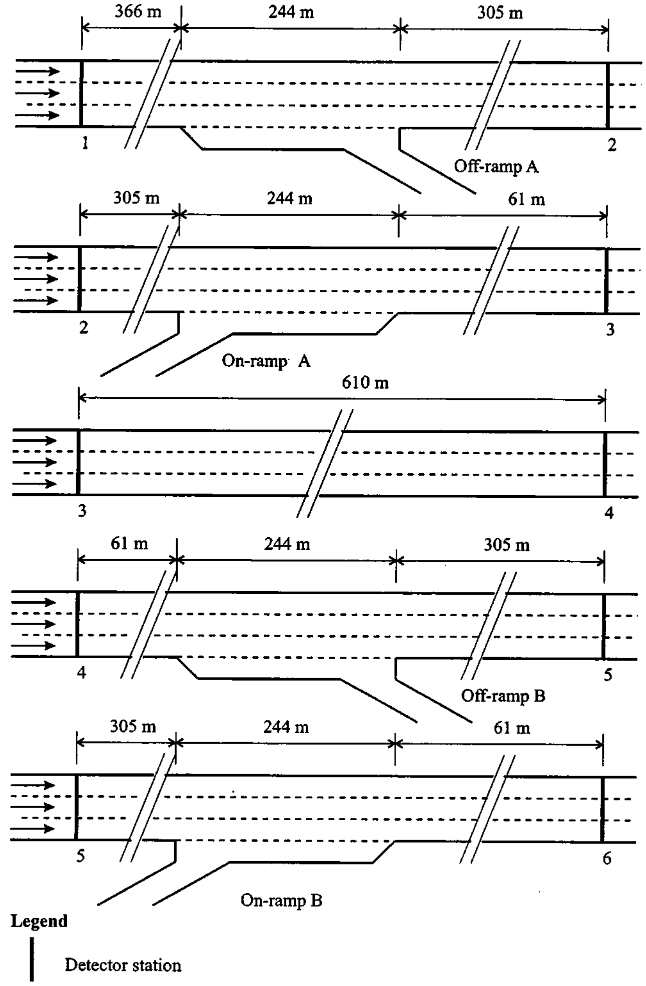

Fig. 6. Layout of urban freeway with ramps evaluated for false alarm performance

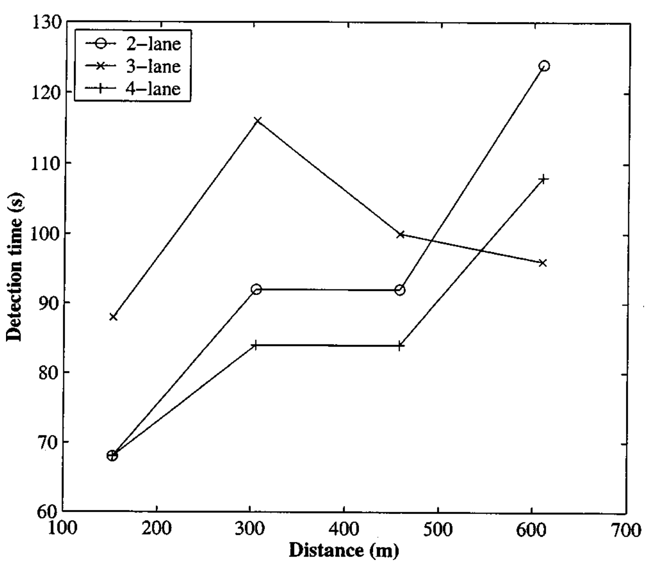

Fig. 5. Variation of detection time with distance for wavelet energy algorithm on two-, three-, and four-lane urban freeway segments when flow rate is 2,000 vph per lane

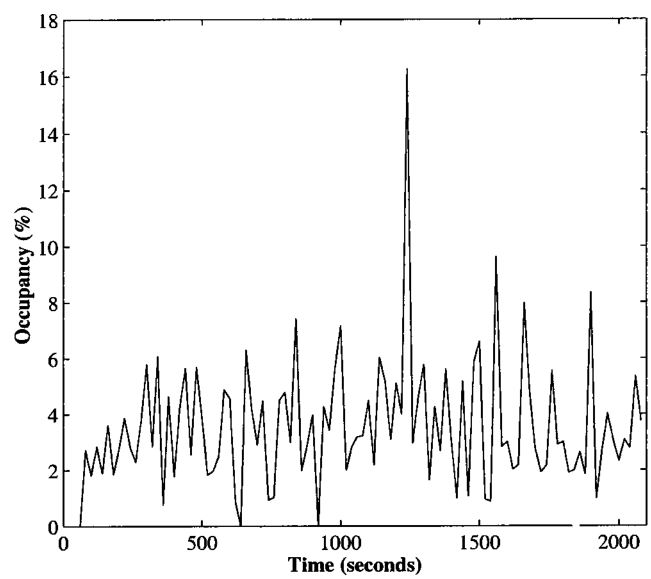

Fig. 7. Lane occupancy plot at downstream detector station on two-lane rural freeway when flow rate is 500 vph per lane

Table 4. Description of Four Simulation Scenarios Used for Evaluating False Alarm Performance on Three-Lane Freeway with Ramps

			On-Ramp Flow Rate (vph)		Off-Ramp Flow Rate (vph)	
Scenario number	Time period number	Entry flow rate (vph)	A	B	A	B
1	1	4,500	300	500	225	450
	2	4,800	300	500	240	480
	3	4,500	300	300	225	450
2	1	5,250	300	500	260	525
	2	5,500	300	500	275	550
	3	5,250	300	300	260	525
3	1	4,000	600	600	200	400
	2	4,500	600	600	225	450
	3	4,000	600	600	200	400
4	1	5,500	600	600	275	550
	2	6,000	600	600	300	600
	3	5,500	600	600	275	550

on sparse information to arrive at a decision. This is further complicated by the often low flow rates on rural freeways that are little impacted by an incident. As a result, passive automatic incident detection algorithms often perform poorly on rural freeways, making them impractical for traffic agencies to implement. Traffic agencies also desire algorithms that require little maintenance and no site-specific calibrations for their optimal performance on rural freeways.

To the best of the writers' knowledge, no automatic freeway incident detection algorithm has been evaluated for rural freeway conditions. In this section, the new wavelet energy algorithm and California algorithm 8 are evaluated on a simulated two-lane rural freeway segment with loop detectors spaced 3,048 m (10,000 ft) apart. The performance of the algorithms is determined for flow rates of 500, 1,000, 1,500, and 2,000 vph per lane. The distance of the incident from the downstream detector station is varied from 152 to 2,744 m. A lane-blocking incident is modeled as the closure of one lane and the 40% reduction in capacity of the adjacent lane. A shoulder incident is modeled by the 40% reduction in capacity of both lanes. Incidents of 5 and 10 min durations are evaluated.

The performance of the wavelet energy algorithm and California algorithm 8 on a two-lane rural freeway with a lane-blocking incident of 10 min duration is given in Table 6. Results are categorized by prevailing flow rates (500, 1,000, 1,500, and 2,000 vph/lane) and distance of the incident from the downstream detector station (152 to 2,744 m). The wavelet energy algorithm performed much better overall than California algorithm 8. When the prevailing flow rate is a low 500 vph per lane, the wavelet energy algorithm detected 18% of the incidents, as compared to zero for the California algorithm. At this low flow rate, there is little or no impact of the incident on traffic patterns upstream and downstream of the incident. A change in the upstream traffic pattern is usually nonexistent because any shock wave created dissipates within 50 to 100 m of the incident. On the downstream side, the shock wave travels much faster and is less likely to be masked by oncoming traffic flow. However, because of the natural variation inherent in traffic flow and the fact that the change in pattern is small, this pattern often cannot be distinguished from normal traffic flow patterns.

This is evident from Fig. 7, which shows a typical lane occupancy time-series plot at the downstream detector station. An incident occurs at time 900 s and persists for 600 s; however, no visible change in the occupancy *pattern* such as a persistent reduction in the occupancy during and after the incident is noticeable from the plot (the spike in the figure is an outlier due to an extraneous factor such as noise in the data and is not an indicator of any change in the occupancy pattern). The wavelet energy algorithm is able to detect some incidents because it considers both occupancy and flow rate readings to create an enhanced and denoised pattern before classifying it. The increased sensitivity of the algorithm, however, does come with a higher false alarm rate. The number of false alarms can be reduced by increasing the threshold t (Fig. 2) used in the wavelet energy algorithm. This can be done easily and in real time by an appropriate logic in the algorithm.

A flow rate of 1,000 vph per lane is typical on many rural freeways under normal operational conditions. Under these con-

Table 5. False Alarm Performance of Wavelet Energy and California Algorithm 8 for Three-Lane Freeway with Ramps

	FALSE ALARMS (OUT OF 1,125 DECISIONS FOR EACH STATION IN SCENARIO)							
	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Station number	WE	Cal.	WE	Cal.	WE	Cal.	WE	Cal.
1	0		0		0		0	
2	0	0	0	0	0	0	0	0
3	0	3	0	1	0	1	0	0
4	0	0	0	1	0	0	0	5
5	0	51	0	130	0	27	0	207
6	0	1	0	0	0	2	0	3
Percent	0	0.98	0	2.34	0	0.53	0	3.82

Note: WE = wavelet energy algorithm; Cal. = California algorithm 8.

Table 6. Performance of Wavelet Energy Algorithm and California Algorithm 8 on Two-Lane Rural Freeway (Incident Duration 10 min; One Lane Blocked, Other Lane's Capacity Reduced by 40%)

		Wavelet Energy Algorithm			California Algorithm 8		
Flow rate (vph per lane)	Location (m)[a]	Detections	False alarms	Detection time (s)	Detections	False alarms	Detection time (s)
500	152	0/5	3/125	—	0/5	0/125	—
	305	0/5	2/125	—	0/5	0/125	—
	610	2/5	6/125	240	0/5	0/125	—
	915	0/5	1/125	—	0/5	0/125	—
	1,220	2/5	0/125	280	0/5	3/125	—
	1,524	1/5	0/125	20	0/5	0/125	—
	1,829	1/5	0/125	20	0/5	0/125	—
	2,134	2/5	0/125	130	0/5	0/125	—
	2,439	0/5	1/125	—	0/5	0/125	—
	2,744	1/5	0/125	180	0/5	0/125	—
Totals		9/50 (18%)	13/1,250 (1.04%)		0/50 (0%)	3/1,250 (0.24%)	
1,000	152	4/5	0/125	150	0/5	0/125	—
	305	5/5	1/125	80	0/5	0/125	—
	610	4/5	0/125	125	0/5	0/125	—
	915	3/5	0/125	153	0/5	0/125	—
	1,220	5/5	0/125	156	0/5	0/125	—
	1,524	3/5	0/125	153	0/5	0/125	—
	1,829	5/5	0/125	164	0/5	0/125	—
	2,134	5/5	0/125	186	0/5	0/125	—
	2,439	5/5	0/125	188	5/5	0/125	452
	2,744	5/5	0/125	152	5/5	0/125	244
Totals		44/50 (88%)	1/1,250 (0.08%)		10/50 (20%)	0/1,250 (0%)	
1,500	152	5/5	0/125	92	0/5	0/125	—
	305	5/5	0/125	76	0/5	0/125	—
	610	5/5	1/125	68	3/5	0/125	246
	915	5/5	0/125	44	3/5	0/125	406
	1,220	5/5	0/125	120	5/5	0/125	500
	1,524	5/5	0/125	120	5/5	0/125	428
	1,829	5/5	0/125	120	5/5	0/125	332
	2,134	5/5	0/125	116	5/5	0/125	236
	2,439	5/5	0/125	160	5/5	0/125	180
	2,744	5/5	0/125	156	5/5	0/125	152
Totals		50/50 (100%)	1/1,250 (0.08%)		36/50 (72%)	0/1,250 (0%)	
2,000	152	5/5	0/125	52	5/5	2/125	160
	305	5/5	0/125	60	5/5	1/125	232
	610	5/5	0/125	64	5/5	0/125	228
	915	5/5	0/125	84	5/5	0/125	168
	1,220	5/5	0/125	68	5/5	0/125	164
	1,524	5/5	0/125	112	5/5	1/125	212
	1,829	5/5	0/125	100	5/5	0/125	176
	2,134	5/5	0/125	136	5/5	1/125	160
	2,439	5/5	0/125	156	5/5	2/125	148
	2,744	5/5	0/125	140	5/5	0/125	148
Totals		50/50 (100%)	0/1,250 (0%)		50/50 (100%)	7/1,250 (0.56%)	

[a]Location of incident from downstream detector station. Distance between detector stations is 3,048 m.

ditions the wavelet energy algorithm detected 88% of the incidents with a false alarm rate of 0.08%. The California algorithm, on the other hand, produced detection and false alarm rates of 20% and zero, respectively, and failed to detect any incident less than 2,479 m from the downstream station, while the wavelet energy algorithm is able to detect 85% of incidents for such distances from the downstream station. The California algorithm will require the detector stations to be spaced at about 610 m apart for its performance to be at par with the wavelet energy algorithm. Such a high density of loop detectors is economically infeasible for rural freeways. Furthermore, the wavelet energy algorithm required an average time of 151 s to detect the incidents, which is acceptable for rural incident management applications. These results show the superiority of the wavelet energy algorithm on rural freeways.

At flow rates of 1,500 and 2,000 vph per lane the wavelet energy algorithm detected all incidents, producing a detection rate of 100%, while the California algorithm produced detection rates of 72 and 100%, respectively. The California algorithm again failed to detect incidents at distances of less than 600 m from the

Table 7. Performance of Wavelet Energy Algorithm and California Algorithm 8 on Two-Lane Rural Freeway (Incident Duration 5 Minutes; One Lane Blocked, Other Lane's Capacity Reduced by 40%)

		Wavelet Energy Algorithm			California Algorithm 8		
Flow rate (vph per lane)	Location (m)[a]	Detections	False alarms	Detection time (s)	Detections	False alarms	Detection time (s)
1,000	152	5/5	0/125	104	0/5	0/125	—
	305	5/5	0/125	120	0/5	0/125	—
	610	3/5	0/125	160	0/5	0/125	—
	915	5/5	1/125	120	0/5	0/125	—
	1,220	4/5	0/125	85	0/5	0/125	—
	1,524	3/5	0/125	146	0/5	0/125	—
1,500	152	5/5	0/125	68	0/5	0/125	—
	305	5/5	0/125	80	1/5	0/125	100
	610	5/5	0/125	80	0/5	0/125	—
	915	5/5	0/125	112	1/5	0/125	120
	1,220	5/5	0/125	96	0/5	0/125	—
	1,524	5/5	0/125	88	4/5	0/125	430
2,000	152	5/5	0/125	44	5/5	0/125	204
	305	5/5	0/125	60	1/5	0/125	80
	610	5/5	0/125	72	5/5	0/125	184
	915	5/5	0/125	80	5/5	0/125	132
	1,220	5/5	0/125	72	5/5	1/125	168
	1,524	5/5	0/125	112	5/5	0/125	192
Totals		85/90 (94.4%)	1/2,250 (0.04%)		32/90 (35.6%)	1/2,250 (0.04%)	

[a]Location of incident from downstream detector station. Distance between detector stations is 3048 m.

downstream detector station at the lower flow rate of 1,500 vph per lane, highlighting its unsuitability for implementation on rural freeways. It also had a false alarm rate of 0.56% at the higher flow rate of 2,000 vph per lane compared with 0% for the wavelet energy algorithm. The detection times for the wavelet energy and California algorithms varied from 44 to 160 and 148 to 500 s, respectively. Except when the flow rate is 500 vph per lane, the detection time for the wavelet energy algorithm on rural freeways is less than 3 min.

Often an incident results in the blockage of a lane for only a short duration of time. For example, a disabled vehicle may block one lane for a few minutes before it is moved onto the shoulder. Detecting such incidents is often more challenging for incident-detection algorithms as the impact of the incident lasts for a shorter period of time. In all the previous evaluations, the incident duration is equal to 10 min. Table 7 shows the performance of the wavelet energy algorithm and California algorithm 8 on a two-lane rural freeway when the lane blockage lasts for 5 min only.

Table 8. Performance of Wavelet Energy Algorithm and California Algorithm 8 on Two-Lane Rural Freeway (Incident Duration 10 Min; No Lane Blocked, Capacity of Each Lane Reduced by 40%)

		Wavelet Energy Algorithm			California Algorithm 8		
Flow rate (vph per lane)	Location (m)[a]	Detections	False alarms	Detection time (s)	Detections	False alarms	Detection time (s)
1,000	152	0/5	0/125	—	0/5	0/125	—
	305	0/5	0/125	—	0/5	0/125	—
	610	1/5	0/125	80	0/5	0/125	—
	915	0/5	0/125	—	0/5	0/125	—
	1,220	2/5	0/125	60	0/5	0/125	—
	1,524	3/5	0/125	113	0/5	0/125	—
1,500	152	3/5	0/125	80	0/5	0/125	—
	305	2/5	0/125	120	0/5	0/125	—
	610	2/5	0/125	60	0/5	0/125	—
	915	2/5	0/125	145	0/5	0/125	—
	1,220	3/5	0/125	127	0/5	0/125	—
	1,524	5/5	0/125	128	0/5	0/125	—
2,000	152	5/5	0/125	40	4/5	0/125	580
	305	5/5	0/125	60	5/5	0/125	508
	610	5/5	0/125	68	5/5	0/125	444
	915	5/5	0/125	72	5/5	0/125	444
	1,220	5/5	0/125	80	5/5	0/125	252
	1,524	5/5	0/125	116	5/5	0/125	276
Totals		53/90 (58.9%)	0/2,250 (0%)		29/90 (32.2%)	0/2,250 (0%)	

[a]Location of incident from downstream detector station. Distance between detector stations is 3,048 m.

Table 9. Performance of Wavelet Energy and California Algorithms Using Real Traffic Data from San Francisco Bay Area Freeway Service Patrol Project's I-880 Database

Detection Rate		False Alarms	
WE	Cal.	WE	Cal.
20/21	19/21	0/480	3/480
95.2%	90.5%	0%	0.63%

Note: WE=Wavelet energy algorithm; Cal.=California algorithm 8.

The detection rate, false alarm rate, and detection times produced by the two algorithms for this scenario are similar to those produced for 10 min incidents recorded in Table 6. This is because the maximum detection time for the energy wavelet algorithm in all cases is 160 s, which is substantially less than the 5 min duration of the incident. As long as the duration of an incident is greater that the detection time, it does not affect the performance of the algorithm in any significant way. The same does not hold true for the California algorithm because its detection time is as large as 430 s. Consequently, as is the case for the 10 min duration incidents, the performance of the wavelet energy algorithm is superior to that of California algorithm 8.

Sometimes incidents produce no lane blockage but only a reduction in the capacity of the lanes. This situation may occur when, for example, a disabled truck is parked on a shoulder, reducing the capacity of the lanes. To study such scenarios on rural freeways, a 40% reduction in capacity of both lanes that lasts for 10 min is modeled for evaluation. The performance of the wavelet energy and California algorithms under such scenario is given in Table 8. The detection rates produced by both the wavelet energy and California algorithms dropped slightly as compared to the case when one lane is blocked (Table 7). This is because an incident that does not block any lanes produces a less severe disruption in traffic flow than an incident that blocks at least one lane. This is especially true when the flow rate is low (1,000 vph per lane). For the same reason, the average detection time by the California algorithm is longer as it takes more time for the congestion to develop and be detected by the algorithm. The detection time of the wavelet energy algorithm is in the range of 40 to 145 s while that of the California algorithm is in the range of 252 to 580 s.

Evaluation Using Real Data

Limited usable real traffic data were available to the writers. Real traffic flow and incident data are extracted from the San Francisco Bay area freeway service patrol project's I-880 database for evaluation of the wavelet energy and California algorithms. Data for 21 incidents that block at least one lane are used to determine detection rate performance, while 4 h of incident-free data are used to ascertain the false alarm rate performance. The time of incident information in the database is inaccurate and therefore cannot be used to determine detection times. The performance of the wavelet energy and California algorithms using real data is shown in Table 9. The wavelet energy algorithm outperformed the California algorithm in both detection and false alarm rate. In particular, the wavelet energy algorithm did not signal any false alarm at all. In contrast, the California algorithm produced a false alarm rate of 0.63% for this small real-data set. It should be noted that this evaluation was also done without recalibrating or retraining the algorithms. Also, note that the algorithms have been trained/calibrated using simulated data only. The detection rate of the wavelet energy incident detection algorithm can be improved when a good amount of real data is available.

Table 10. Performance Vector for Assessment of Algorithm Portability

Wavelet energy algorithm	California algorithm 8
0,0,89	0,0,320
0,0,84	0,0.17,157
0,0,94	0,0.5,102
0,0,69	75,0,248
0,0,74	0,0.17,175
0,0,100	0,0.17,113
0,0,71	65,0,304
0,0,86	0,0.17,171
0,0,86	0,0.67,112
82,1.04,145	100,0.24,inf
12,0.08,151	80,0,348
0,0.08,107	28,0,310
0,0,97	0,0.56,180
17,0.13,122	100,0,inf
0,0,87	80,0,217
0,0,73	13,0.13,160
80,0,84	100,0,inf
60,0,110	100,0,inf
0,0,73	3,0,417

Note: inf=no incidents are detected and detection time is theoretically equal to infinity.

Performance Summary and Conclusion

Transferability or portability is a qualitative property of a freeway incident-detection algorithm that determines how well the algorithm performs across various traffic flow and roadway geometry conditions. In all the tests performed in this evaluation the algorithms are not recalibrated or retrained. Thus, a good way to assess the algorithms' portability is to compare their *performance vectors* across different test scenarios. A *performance vector* is defined as a vector with three performance elements: the percentage of missed detections (equal to 100 minus the detection rate); the false alarm rate; and the detection time. The smaller the value of each element, the better the performance. Table 10 gives the performance vectors for the wavelet energy and California algorithms for the various scenarios evaluated in this research (extracted from Tables 1–3 and 6–8). The wavelet energy algorithm performed consistently well across all scenarios, including typical rural and urban freeway conditions. Furthermore, for any given scenario the wavelet energy algorithm outperformed California algorithm 8. This result establishes the portability of the wavelet energy algorithm and demonstrates its excellent performance for urban freeways across a wide range of traffic flow and roadway geometry conditions regardless of the density of the loop detectors.

To the best of the writers' knowledge, no systematic evaluation of any existing incident-detection algorithm on rural freeways has ever been published in the literature before. This paper presents the first investigation of this kind. Considering the difficulty in automatic detection of incidents on rural freeways, the new wavelet energy algorithm performs well on such freeways, with detectors being placed a large 3 km apart, except when the flow rate is lower than 500 vph per lane. It is unlikely that a passive incident detection algorithm based on loop detector data can perform better than the wavelet energy algorithm in such low flow rate conditions; the traffic is just not affected enough to be detected reliably.

It is concluded that the new wavelet energy algorithm is not only highly robust and suitable for practical implementation on large urban freeway systems, but also suitable and cost-effective for implementation on most rural freeways.

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