A hybrid model using logistic regression and wavelet transformation to detect traffic incidents

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ABSTRACT

This research paper investigates a hybrid model using logistic regression with a wavelet-based feature extraction for detecting traffic incidents. A logistic regression model is suitable when the outcome can take only a limited number of values. For traffic incident detection, the outcome is limited to only two values, the presence or absence of an incident. The logistic regression model used in this study is a generalized linear model (GLM) with a binomial response and a logit link function. This paper presents a framework to use logistic regression and wavelet-based feature extraction for traffic incident detection. It investigates the effect of preprocessing data on the performance of incident detection models. Results of this study indicate that logistic regression along with wavelet based feature extraction can be used effectively for incident detection by balancing the incident detection rate and the false alarm rate according to need. Logistic regression on raw data resulted in a maximum detection rate of 95.4% at the cost of 14.5% false alarm rate. Whereas the hybrid model achieved a maximum detection rate of 98.78% at the expense of 6.5% false alarm rate. Results indicate that the proposed approach is practical and efficient; with future improvements in the proposed technique, it will make an effective tool for traffic incident detection.

1. Introduction

In many countries, traffic incidents are one of the major reasons for traffic congestion, property damage worth millions of dollars and large number of deaths and injuries every year [1–3]. Traffic incidents are non-periodic and pseudo-random events that cause traffic jams and affect the overall performance of the road network, often leading to secondary incidents [4]. The probability of traffic incidents is higher during peak hours. Many major cities in the U.S. have a traffic management system, which includes traffic characteristic detectors and a centralized operations center for monitoring. These detectors consist of video cameras, bluetooth sensors, flow detector sensors, etc., which can capture such traffic characteristics as traffic speed, occupancy, and volume [5]. Automatic techniques for incident detection, using this data, are not widely used yet. However, reliable and quick detection of incidents can prove very useful in incident management on roadways so that an emergency crew can be sent to the incident location for obstruction clearance and medical assistance. These techniques also can help to manage detours efficiently and enable better management of traffic and road networks [6,7].

Many researchers have worked on the problem of real-time incident detection techniques using the real-time traffic data. A survey aimed at understanding the usefulness and sufficiency of current AID methods, was conducted on traffic management centers (TMC) professionals [8]. 90% of the survey respondents felt that the currently available methods of incident detection were insufficient. Hence research efforts aimed at developing accurate and robust AID systems, must be increased. The main issue is the confidence level with which the incident can be predicted. Incident detection can be seen as a classification problem with two outcomes: incident detected or incident not detected. Based on the available data (volume, occupancy, speed, etc.), algorithms decide whether the data represents an incident or not. Misclassification of either of the two reduces the reliability and usability of the system. Hence, the objective is to develop a reliable, automatic system for traffic incident detection that analyzes the data and predicts incidents efficiently with a high level of confidence [9].

A logistic regression model is suitable when the outcome can take only a limited number of values. Regarding traffic incident detection, the outcome is limited to only two values, the presence or absence of an incident. A logistic regression model is a generalized linear model (GLM) with a binomial response and a logit link function. A framework

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is presented in [10] to use the logistic regression model for incident prediction in transportation systems.

Wavelet transform is a powerful technique for feature extraction from data that are characterized by frequent additive white noise or other type of noise such as Gaussian or impulsive noise. This technique has been studied in recent years for various applications of intelligent transportation systems, including incident detection, data aggregation, data compression and denoising. Wavelet transform has many attractive properties, such as multiresolution analysis, time frequency localization, and multirate filtering. Wavelet-based denoising techniques are well known, especially in the field of image processing.

This paper proposes a hybrid model using logistic regression and wavelets for traffic incident detection. We investigate the effect of data filtering when using wavelets on the performance of an incident detection model. Data is denoised using wavelets, and the performance of the model is studied using the denoised data. The literature survey also suggests that for some of the incident detection algorithms, feature extraction using discrete wavelet transform (DWT) increases the detection rate. A case study is conducted using historical traffic data to analyze the reliability and efficiency of the proposed model. Main contribution of this paper is how the performance of a well-known automatic incident detection (AID) tool — logistic regression, can be improved substantially by integrating it with the wavelet-based feature extraction, and study of its potential use for AID systems.

The rest of the paper is organized as follows: Section 2 provides a comprehensive overview of the relevant literature on the topic, Section 3 builds the necessary mathematical background of logistic regression, Section 4 provides introduction to wavelet analysis and transform. Section 5 discusses the framework and methodology used in the paper, Section 6 discusses the results, and finally Section 7 concludes the paper.

2. Literature survey

Over the years, many algorithms have been proposed for traffic incident detection. Traffic sensors generally give information about traffic occupancy, speed, volume and flow rate. Traffic occupancy indicates the fraction of time that a particular location is occupied by a vehicle. Flow rate indicates the number of vehicles passing through a location in a unit amount of time. The methods proposed for incident detection range from simple threshold comparisons to more complex model-based predictions.

An algorithm for predicting freeway crashes from loop detector data by using matched case–control logistic regression identified more than 69% of the crashes [11]. Another algorithm for automatic freeway incident detection, based on fundamental diagrams of traffic flow was proposed in [12]. Authors focused on finding a new set of variables for the feature generation. The new variables, uncongested and congested regime shifts (URS and CRS), were generated by conducting coordinate transformation on loop-detected flow and occupancy measurements. Similarly, a real-time crash prediction model for the ramp vicinities of urban expressways was proposed in [13].

Recently, researchers shifted their focus towards model-free detection techniques involving fuzzy logic theory, neural networks, or a combination of both. In the fuzzy logic approach, the objective is to build a fuzzy knowledge with the available historical data and come up with some fuzzy rules. These rules are then processed by a fuzzy logic system to identify and predict the outcomes. A study was conducted to evaluate the applications of fuzzy set theory to improve existing incident detection algorithms in [14].

Artificial neural networks (ANNs) are known to be powerful with regard to pattern recognition and classification problems. They act like a model-free black box. They are adaptive, and grab the structure of data quickly and efficiently. A methodology was proposed for automated detection of lane-blocking freeway incidents using artificial neural networks (ANNs) in [15]. To classify the traffic data, authors developed

three types of neural network models, namely, the multi-layer feedforward (MLF), the self-organizing feature map (SOFM), and adaptive resonance theory 2 (ART2). Among the three ANNs, MLF was found to give best results. Another study evaluated the adaptability of three neural network (NN) models for aid systems: a multilayer feedforward NN (MLFNN), a basic probabilistic NN (BPNN) and a constructive probabilistic NN (CPNN) [16]. Results of this study showed that the MLFNN model had the best incident detection performance at the development site while CPNN model had the best performance after model adaptation at the new site. In [17] researchers developed a neural network model for estimating secondary accident likelihood. Results suggested that traffic speed, duration of the primary accident, hourly volume, rainfall intensity, and number of vehicles involved in the primary accident were the top five factors associated with secondary accident likelihood.

Nowadays, advanced traffic management systems capture and store video image data. This is in addition to the traditionally captured traffic data, and can supplement and improve data inputs in transportation modeling. Existing transportation models can benefit from video image detection technology, and improved modeling and analysis can be done, provided the accuracy of video stream. A study investigating accuracy of traffic video streams and its benefits in transportation modeling was done in [18]. Video-based AID systems are increasingly being used in intelligent transportation systems. Two new video-based automatic incident detection algorithms, the individual detection evaluation (INDE) and combined detection evaluation (CODE) algorithms were developed [19]. Pursuing the subject further, a total of 160 incidents were collected along the 15-km central expressway (CTE) in Singapore to develop two new dual-station algorithms: the combined detector evaluation (CODE) and the flow-based CODE algorithms [20]. A literature review was performed in [21] analyzing the effects of external environmental factors, namely, static shadows, snow, rain, and glare, on the accuracy of video-based AID.

An acoustic signal processing based automatic incident detection technique was developed in [22]. This involved processing of acoustic signals and recognizing accident events from the background traffic events. The classification testing resulted in a maximum of 99% accuracy. Improved nonparametric regression (INPR) algorithm was used for forecasting traffic flows and its application in automatic detection of traffic incidents in [23]. Performance evaluations resulted in lower average prediction error and lower average computing times as compared with other forecasting algorithms.

Researchers are increasingly exploring the potential of wavelet transform in transportation applications. Wavelet transform is a powerful tool for feature extraction, data denoising and data compression. Wavelet decomposition technique was successfully incorporated to compress the ITS data in [24]. Wavelet transform for feature extraction was used to improve volume adjustment factors for rural roads in [25]. Researchers investigated an Adaptive conjugate gradient neural network model (ACGNN) models for traffic-incident detection problems in [26]. They tried the algorithm with various combinations of traffic data series, such as traffic volume, speed, and occupancy. Results indicated the best incident detection rate of 91.1% with the combination of all three parameters, and a false alarm rate of 5.1%. Further enhancement was done by combining DWT and linear discriminant analysis(LDA) with ACGNN [12]. The new computational model was based on preprocessing the traffic data by DWT and LDA, followed by ACGNN. Results were much better, with a higher detection rate of 97.8% and a lower false alarm rate of 1%. Another approach integrating fuzzy, wavelet, and neural computing techniques was proposed for AID in [27]. In this methodology, a wavelet-based denoising technique was used to get rid of unwanted noise in the data from traffic sensors.

A methodology was proposed in [28] for enhancing traffic-incident detection algorithm based on fuzzy neural networks by using wavelets. Authors showed that the performance of a fuzzy neural network algorithm could be improved through preprocessing of data using a

wavelet-based feature-extraction model. In this approach, discrete wavelet transform (DWT) denoising and a feature-extraction model were combined with the fuzzy neural network approach.

Use of wavelet analysis has also been explored in traffic flow forecasting related problems. A new methodological approach was proposed for short-term predictions of time series volume data based on the stationary wavelet-based denoising process and a self-organizing fuzzy neural network [29]. A hybrid wavelet packet-autocorrelation function (ACF) method was proposed for analysis of traffic flow time series in [30]. This DWPT-based approach combined with a wavelet coefficients penalization scheme and soft thresholding was used for denoising the traffic flow data.

The discussion above highlights various AID techniques researched and also makes a case for the wavelet based feature extraction. The need for real-time and computationally less expensive algorithm helps us in the selection of logistic regression based model coupled with wavelet analysis.

3. Mathematical background

3.1. Logistic regression

Logistic regression is type of regression analysis where categorical outcomes can be predicted based on certain predictors [31]. Probabilities of the possible outcomes are modeled, using logistic functions, as a function of independent variables. Logistic regression can be binomial or multinomial. Logistic regression uses a link function which transforms the limited range of a probability $[0, 1]$, into $(-\infty, +\infty)$.

3.2. Logit transformation

In the desired model, probabilities (p_i) should depend on the predictors or covariates (x_i). To start with, a simple linear model can be assumed, where p_i is a linear function of x_i as:

$$p_i = \beta \cdot X_i \qquad (1)$$

where β is a vector of regression coefficients. This model is called linear probability model, and it is generally estimated using ordinary least squares (OLS) methods. Problem with this model is that, probability on the left hand side can take value only between zero and one, whereas the right hand side can take any real value. This problem can be solved by following two steps. Instead of probability, consider odds as:

$$Odds_i = \frac{p_i}{1-p_i}$$

and next, take log of this odd to get the logit or log-odds:

$$\eta_i = logit(p_i) = log\frac{p_i}{1-p_i} \qquad (2)$$

η_i has the range from $+\infty$ to $-\infty$.

3.3. Logistic regression model

Suppose the independent observations y_i are realization of random variable Y_i having a binomial distribution

$$Y_i = B(n_i p_i) \qquad (3)$$

Now, assuming that logit of the probability p_i is dependent linearly on the predictors, the equation becomes:

$$\eta_i = logit(p_i) = \beta \cdot X_i \qquad (4)$$

Model defined by the Eqs. (3) and (4) forms a generalized linear model (glm) with binomial response and link logit. Logistic regression is a special case of generalized linear model. The conditional distribution $y|x$ is a Bernoulli distribution as the dependent variable is binary. Also, the error in logistic regression is distributed by the standard logistic distribution (logit function) rather than the standard normal distribution as in case of a probit regression.

4. Wavelet feature extraction

Data obtained through loop detectors sometimes has added white noise or Gaussian noise or impulsive noise, based on the type of the sensor [32,33]. For the purposes of traffic analysis, prediction, and control, denoised and smoothened data is necessary. Wavelet transform techniques provide an effective way to denoise, and have been applied successfully in various areas, especially for image processing. In this incident detection model, wavelet transform is used to denoise and smooth traffic data. This denoising technique is used as a pre-step to the incident detection algorithm. In this paper, data obtained through this preprocessing is referred to as 'filtered' data.

Noise is a random error that gets added to the observed data. This can be due to instrumental errors, technology limitations, human factors, or natural phenomenon, such as atmospheric disturbances. Denoising algorithms try to separate the original signal and the additive white noise. Wavelet transform converts the data into a wavelet basis by decomposing it into the wavelet and scaling coefficients [34]. Scaling coefficients, also called approximation coefficients, are large in magnitude; in contrast, wavelet coefficients are very small in magnitude, and represent variations in the signal [35]. As the first level of transform pertains to differences in high frequencies, the noise can be handled effectively at that level. By appropriately choosing the threshold and applying them on the wavelet coefficients, noise is eliminated. Denoised signal can be obtained by applying inverse wavelet transform on approximations and thresholded wavelet coefficients. The main steps of wavelet-based denoising are as follows:

1. Apply wavelet transform to the data and decompose it into approximation and detail coefficients
2. Select an appropriate threshold and apply the thresholding (either soft or hard depending on the data and objective)
3. Inverse wavelet transform using approximation and thresholded wavelet coefficients.

4.1. Discrete wavelet transform (DWT)

There exist many types of wavelet transforms among which DWT is the most commonly used for discrete signals. This section describes the mathematical theory and methodology to compute DWT briefly [9]. We know that any function $f \ \epsilon \ L^2(R)$ can be written as linear combination of elementary functions $\psi_{j,k}(x)$:

$$f(x) = \sum_{j,k} w_{j,k}\psi_{j,k}(x), \qquad j,k \ \epsilon \ \mathbb{Z} \qquad (5)$$

where $w_{j,k}$ is the set of coefficients. Subscripts j and k are used to indicate the two dimensional decomposition for providing resolution in both time and frequency domain. Now we can obtain elementary function from the mother wavelet as follows:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \qquad a > 0, \ \ b \ \epsilon \ \mathbb{Z} \qquad (6)$$

where a and b are integers and represent scaling and translation respectively. For most practical uses, scaling is done in powers of

Table 1
Dataset for incident detection.

Occupancy	Volume	Avg speed	Incident
5	1848	61.6	0
5.8	1607	60.2	0
5.2	1840	63	0
5.2	1805	63.6	0
3.8	1945	36	1
4	1652	21.2	1
3.6	1744	23.8	1
3	1649	21	1
2.6	1770	22.4	1
3.2	1770	25.6	0
2.8	1866	24.6	0
2.4	1206	25.8	0
2.4	1474	28.6	0
2.4	1845	25.8	0
2	1971	27.8	0
2.4	1825	24.8	0
2.4	1858	24.6	0
2.6	1794	28.2	0
2.2	1919	26.2	0
1.6	1768	45.8	0
5	1959	49.8	0
5.8	1727	60	0
5.2	1692	65.6	0

two, hence the dyadic version of the above equation is written as follows:

$$\psi_{j,k}(x) = 2^{\frac{j}{2}}\psi\left(2^j x - k\right), \quad j, \ k \ \varepsilon \ \mathbb{Z} \tag{7}$$

Now if $\psi_{j,k}$ forms an orthonormal basis then the coefficients of DWT can be computed by taking inner product of the function $f(x)$ with the wavelet $\psi_{j,k}$:

$$w_{j,k} = f, \psi_{j,k} = \int_R f(x)\psi_{j,k} \ dx \tag{8}$$

4.2. Threshold selection

There are two types of thresholding:

• Hard thresholding (keep or kill)

$$Thr = \begin{cases} median(abs(detail \ at \ level \ 1)); & if \ nonzero \\ 0.05 \ max(abs(detail \ at \ level \ 1)); & otherwise \end{cases} \tag{9}$$

In hard thresholding, the coefficients below a certain threshold are set to zero and the magnitudes of the wavelet coefficients above the threshold are left unchanged.

$$T_d^{hard} = \begin{cases} d \ ; & |d| > Thr \\ 0 \ ; & |d| \le Thr \end{cases}$$

• Soft thresholding (shrink or kill)

$$Thr = \sqrt{2.\log(n)}$$
$$and \quad n = prod(size(x)) \tag{10}$$

In soft thresholding, the coefficients below a certain threshold are set to zero whereas the remaining coefficients are reduced by an amount equal to the value of the threshold.

$$T_d^{soft} = \begin{cases} sgn(d)(|d| - Thr) \ ; & |d| > Thr \\ 0; & |d| \le Thr \end{cases}$$

Hard thresholding is default for compression whereas soft thresholding is recommended for denoising of a given signal.
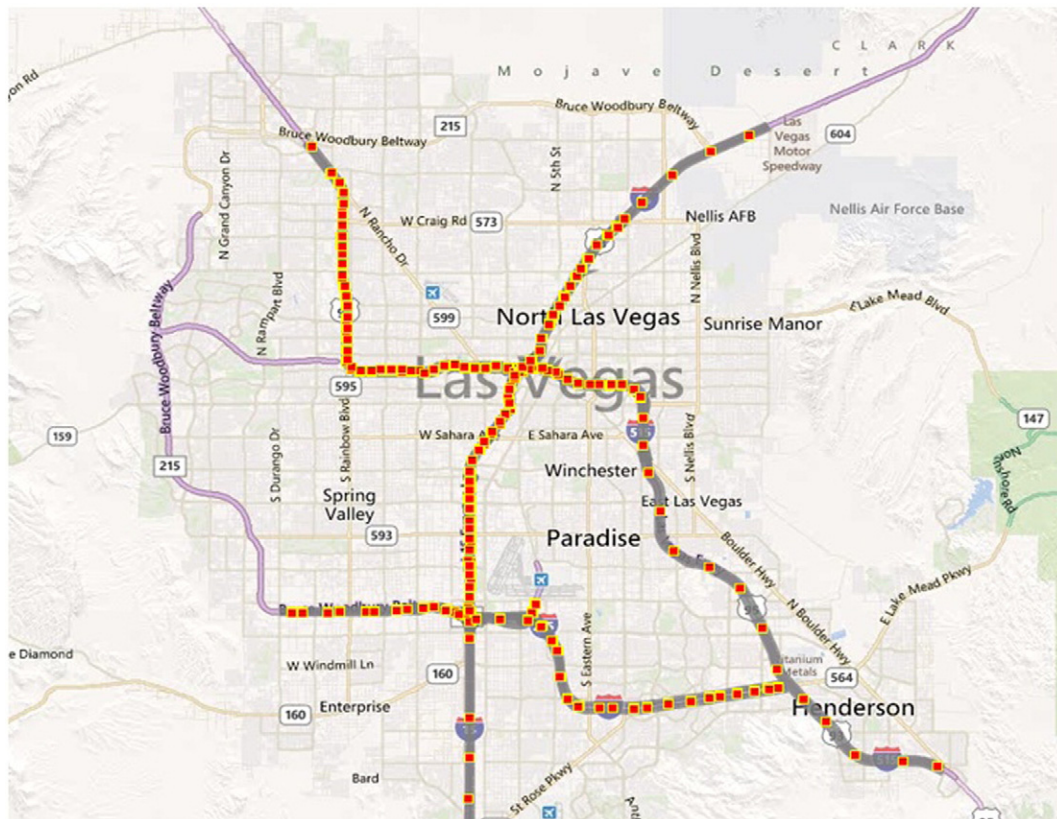
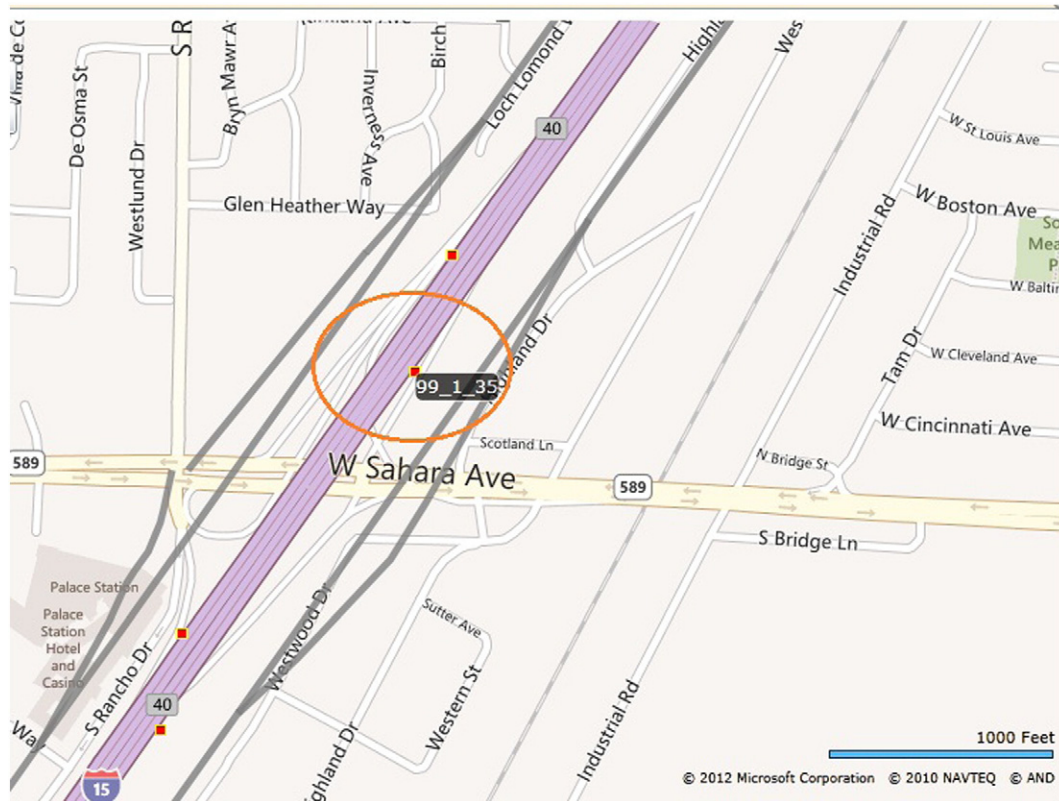**Fig. 1.** Traffic sensors on freeway (Las Vegas area).

Fig. 2. Identified crash site.

5. Framework and methodology

In the sample data set shown in Table 1, the incident column has a value either of zero or one. Zeros indicate non-incident or normal traffic behavior, whereas ones indicate a traffic incident. To incorporate the prolonged effects of incidents, such as congestion or lane blocking, the incident column was assigned a value of 'one' for five additional readings along with the actual reading in which the incident happened.

Logistic regression is applied for incident detection, using only raw data. Further, traffic data is filtered using DWT, and filtered data is used for incident detection.

5.1. Data source and characteristics

Fig. 1 shows the traffic sensors that are placed along freeways US-95 and I-15 in the Las Vegas area. This data contains lane wise speed, occupancy, and volume along with the time stamp. This data is averaged and updated at every 2 min interval [36]. It is available for each of the detectors placed along the freeway.

Traffic incident database gives details about the time and location of the traffic incidents on the freeway. The data is analyzed, and a high probability crash location is identified as I-15 North bound, past Sahara (Fig. 2). Two separate data sets were combined, containing traffic parameters and traffic incidents for April 2012. Combined database looked like Table 1.

6. Results and discussion

The following are the results of logistic regression model applied on traffic data for incident detection, using average speed, volume, and occupancy as predictors. Table 2 gives the maximum likelihood estimation for the model.

Table 3 provides estimated values of coefficients and standard error for the variables.

For a particular set of data input, model gave back a probability of the incident occurring at that instant. The model was then fine tuned and a threshold probability was obtained. If the probability given by the model at a particular instant was higher than the threshold value, then it was assumed that an incident had occurred and vice versa.

For analyzing the effect of various traffic parameters as predictors in the model, different combinations of these parameters were tested separately. For analysis purpose threshold probability was fixed at 0.5 for all the combinations. Table 4 provides the incident detection rate and false alarm rate for various combinations of traffic parameters

Table 2
Maximum likelihood estimates.

Parameter/test	Value
Dependent variable	Incident
Weighting variable	None
Number of observations	1000
Iterations completed	8
Log likelihood function	−20.13
Restricted log likelihood	−42.10
Chi squared	43.95
Degrees of freedom	3
Prob[ChiSqd > value]	.00
Hosmer-Lemeshow chi-squared	2.83
P-value	.94 (8 df)

Table 3
Estimation of coefficients and Std. error.

Variable	Coefficient	Std. error	b/Std. er.	P[|Z|>z]	Mean of X
Constant	.7329	4.0302	.182	.8557	
Occupancy	−.0673	.0966	−.697	.4860	11.07
Volume	.0034	.0014	2.384	.0171	1224.24
Speed	−.1392	.0610	−2.281	.0225	56.46

Table 4
Incident detection results using logit model.

Traffic data	Incident detection rate (%)	False alarm rate (%)
Volume (Veh/h)	18.87	0.99
Occupancy (%)	50.94	5.59
Avg Speed (miles/h)	58.49	5.26
Avg speed + occupancy	60.38	4.61
Avg speed + volume	64.15	5.26
Occupancy + volume	54.72	4.61
Avg speed + occupancy + volume	67.15	4.93

Table 5
Incident detection results using the hybrid model.

Traffic data	Incident detection rate (%)	False alarm rate (%)
Volume (Veh/h)	32.14	3.45
Occupancy (%)	60.71	6.90
Avg speed (miles/h)	53.57	6.21
Avg speed + occupancy	71.43	4.14
Avg speed + volume	71.43	4.83
Occupancy + volume	67.86	4.83
Avg speed + occupancy + volume	81.00	2.8

using only logistic regression and a probability threshold value of 0.5. The highest detection rate of 67.15% was observed while using a combination of volume + speed + occupancy.

Table 5 shows incident detection results using logistic regression after wavelet based feature extraction of the data by DWT, at a fixed probability threshold of 0.5. The highest detection rate of 81.0% was observed using a combination of volume + speed + occupancy.

The new hybrid model combining DWT and logistic regression yielded a better incident detection rate of 81% as compared to 67.15% when using only a logistic regression model. The false alarm rate in this hybrid model was also on the lower side (2.8%) when compared to the logistic regression model alone (4.93%). The best results were obtained for the combination all three traffic parameters: traffic volume, avg speed, and occupancy. However, as observed in Tables 4 and 5, for each of the parameters and their combinations, the hybrid model yielded a better detection rate and fewer false alarms.

Probability threshold value was varied from one to zero to obtain the receiver operating characteristic (ROC) curves of the model. Fig. 3 shows the variation of incident detection rate against a false alarm rate for the logistic regression model, as the threshold probability varies from 1 to 0. This ROC curve shows a maximum detection rate of over 95% at the expense of 14% false alarm rate.

Fig. 4 shows the variation of incident detection rate against a false alarm rate for the hybrid model, as the threshold probability varies from 1 to 0. ROC curve shows a maximum detection rate of over 95% at the expense of 14% false alarm rate.

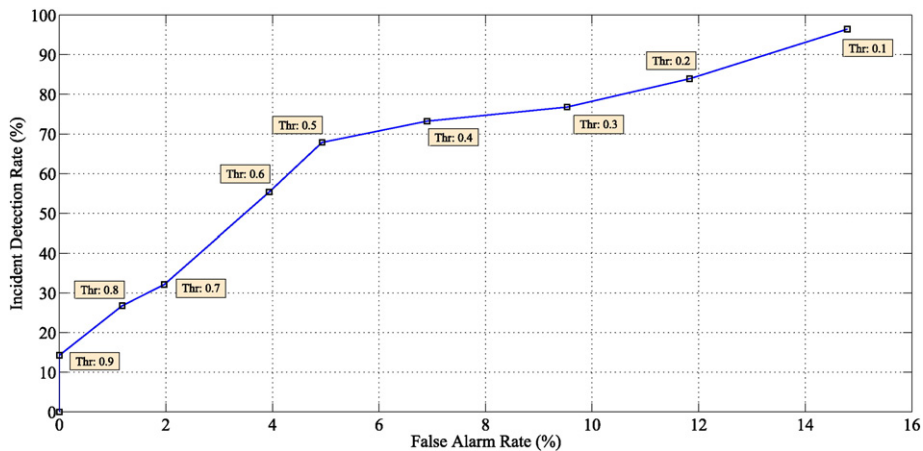Fig. 5 compares the ROC curves of the logistic regression and the proposed hybrid model.

Fig. 3. Incident detection vs. false alarm rate using logistic regression model.
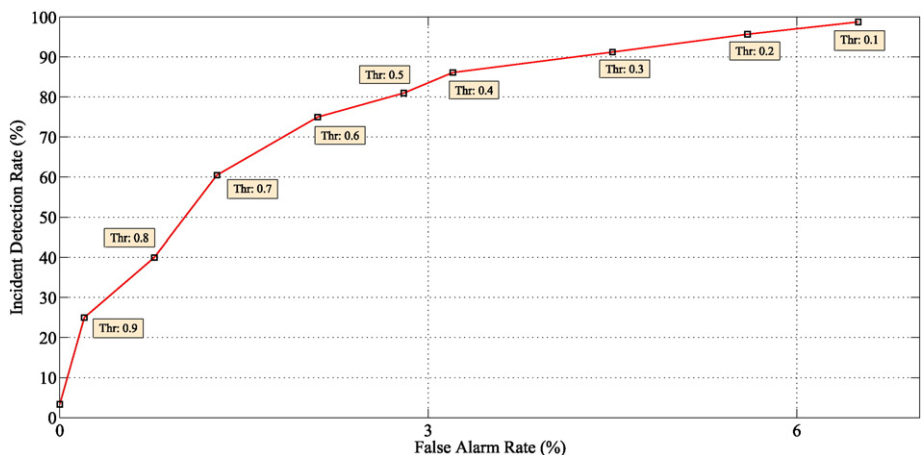

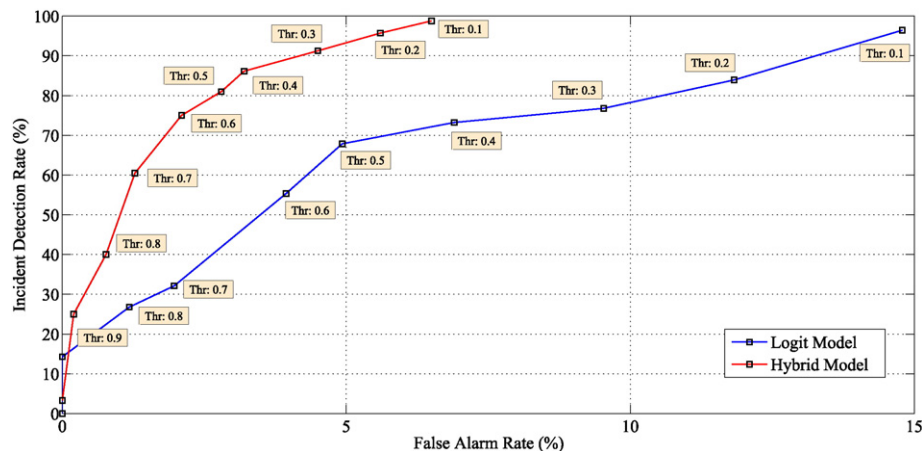Fig. 4. Incident detection vs. false alarm rate using hybrid model.

Fig. 5. Comparison of logistic regression and the proposed hybrid model.

7. Conclusion

Main objective of this research was to study wavelet based feature extraction for improving the performance of logistic regression technique for traffic incident detection. For studying the potential use of logistic regression for AID problem, various combinations of traffic parameters: traffic volume, occupancy, and avg speed were used and tested. Receiver operating characteristic (ROC) curves were plotted by varying the probability threshold, and it showed a maximum detection rate of 95.4% at the cost of 14.5% false alarm rate. A new hybrid model was proposed that combined two different computational approaches: wavelet transform and logistic regression. It was observed that using the wavelet based denoising technique, before feeding the data in logistic regression model, gave better detection rates and lower false alarm rates. ROC curves were plotted by varying the probability threshold value and were compared with the ROC curve for unprocessed data. The hybrid model achieved a maximum detection rate of 98.78% at the expense of 6.5% false alarm rate. It was observed that at each fixed false alarm rate, hybrid model gave a better incident detection rate. The main advantage of using the hybrid model was in achieving the same detection rates at a much lower false alarm rates. Hence logistic regression technique along with wavelet based feature extraction performs much better than simply logistic regression for traffic incident detection.

This study showed that logit models along with wavelet based feature extraction have great potential for AID applications. The proposed hybrid incident detection algorithm can be further scaled for real-time detection purposes. A cost analysis of false alarms can be done, and an acceptable balance can be struck between the false alarm rates and the incident detection rates.

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