I −20 マクロ交通流モデルを統合したニューラルネットワークモデルによる高速道路上のインシデント検出手法の開発

Development of an Automatic Incident Detection Algorithm by Integration of Neural Network Model and Macroscopic Simulation Continuity Equation

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[抄録] 高速道路上のインシデントを自動的に検知するために、逆伝搬法を基本とするニューラルネットワークモデルを用いた予備的な手法の開発を行った。バンコクにおける高速道路の1区間を解析対象として、インシデントの検出における、交通量地点速度、密度、あるいは時間占有率などといった様々な交通変量がニューラルネットワークモデルの入力信号としていかに有効であるかを調査した結果、車両感知器によって計測される地点速度データとマクロ交通流モデルから推定される密度データが最も効果的であることが判明した。開発されたモデルは、従来の代表的な検出手法とも比較され有用性が確認されている。また、学習のデータサイズに関する検討も行われている。

[Abstract] A prototype automated incident detection algorithm is developed to predict the transition from incident free to incident state by training a neural network model by Back Propagation paradigm for a section of Second Stage Expressway, Bangkok. The effectiveness of different traffic flow variables like volume, spot mean speed, density and occupancy as input to neural model in order to detect the transition from incident free to incident state is investigated. The neural model trained using spot mean speed data acquired from traffic detector and density estimated using Continuity equation of Macroscopic Model is found to be the most efficient. The trained neural model is evaluated using test data and is compared with conventional incident detection algorithms. Finally, the effect of data size on the performance of neural model is investigated.

[キーワード] インシデント検知手法・ニューラクネットワークモデル・逆伝搬法・流量保存則・マクロ(巨視的)交通流モデル・ミクロ(微視的)交通流モデル・FRESIM

[Keywords] Incident Detection, Neural Networks, Back Propagation, Continuity Equation, Macroscopic Model, Microscopic Traffic Simulation Model, FRESIM

Introduction

One of the major sources of freeway delay is non-recurring congestion caused by incidents. Early and correct detection of incidents can result in substantial reduction in delay to motorists. Secondary crashes that take place because of sudden change in traffic conditions during incidents can also be minimized. Considering this the importance of the incident detection in a freeway surveillance system cannot be overemphasized. Automated incident detection algorithms have a long history. Some of the very first incident detection algorithms developed are based on comparison of traffic flow parameters like proposed by Payne and Tignor (1) and by Levin and Krause (2) on the principle that an incident is likely to increase the upstream occupancy and decrease the downstream occupancy. One of the most widely used algorithm of this type is California algorithm (3). In an attempt to reduce the false alarm rate Levin and Krause (4) incorporated the historical probability distribution and proposed to use Baye's rule. Dudek and Messer (5) used mean and standard deviation of occupancy for the last three to five minutes and detected an incident when the value differs significantly from mean in terms of standard deviation. Ahmed and Cook (6) on the basis of data collected from surveillance centers developed an auto-

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regressive time series model to represent traffic flow on a freeway. Data that significantly deviates from the predicted one triggers an alarm. More recently, Balke *et al.* (7) investigated the feasibility of using probe vehicles to collect travel time information for freeway incident detection. Historical travel time patterns are compared to travel time of probe vehicle and the difference between the two is used to predict the incident on the facility.

Most of the conventional detection techniques used mathematical models formulated based on observations of traffic data during incidents, with parameters calibrated with field incident data. They often have difficulties in distinguishing traffic data during incidents from similar patterns caused by other traffic disturbances such as shock waves (8). The partial success of conventional techniques led researchers to search for more sophisticated techniques. One of those techniques applied is the use of Artificial Neural Networks (ANN) for incident detection. ANN excel at problems involving patterns-pattern mapping, pattern completion and pattern classification. Incident detection is a typical pattern recognition problem and can be benefited from the application of neural network models. A few researchers have attempted to exploit this potential and the results are quite promising. Stephanedes and Liu (9) developed a freeway incident detection algorithm using back propagation neural network. The network was trained with real-time occupancy and volume counts from pairs of adjacent traffic detector stations. Cheu and Ritchie (8) investigated automated detection of lane blocked incidents on freeway using ANN. Different types of ANN models were tested and the multi-layer feed forward (MLF) was found to have the highest potential for incident detection. Algorithm performance, in terms of detection and false alarm rate was found superior to most of the conventional algorithms. However, still these techniques need substantial improvement, especially in the area of false alarm rate before practical implementation.

In order to mitigate shock waves effect and short term traffic fluctuations primarily responsible for false alarms, this study integrated ANN model with continuity equation of macroscopic model. The macroscopic traffic model was originally developed by Payne (10, 11) represents traffic flow in terms of aggregate measures such as density, space mean speed and volume. The continuity equation of macroscopic model is capable of reflecting different traffic states with reasonable accuracy, as density is a unique traffic flow parameter. The estimated densities, using continuity equation, along with the other traffic data obtained through traffic detectors spanned over twelve time steps, with a time step size of fifteen seconds, are used as input to ANN model. The improvement in the performance of ANN model with the use of density as input is because density fluctuates less compared to other traffic variables e.g., traffic volume. The continuity equation used for the estimation of density is,

$$k_i^{n+1} = k_i^n + \frac{\Delta t}{\Delta x_i}\left[q_{i-1}^n - q_i^n + r_i^n - s_i^n\right] \tag{1}$$

where,

k_i^n = Density i.e., the number of vehicles per length unit (veh/km)

r_i^n = On-ramp volume, s_i^n = Off-ramp volume

n = Discrete time step, Δt = Time step size

q_{i-1} and q_i = Traffic volume entering and leaving section, respectively,

Δx_i = Section length

The performance of the trained neural model is compared with the California incident detection algorithm. The California algorithm consists of three comparison tests. An incident is detected when (a) when upstream occupancy is significantly higher than downstream occupancy both in absolute value and relative to upstream occupancy and (b) when downstream occupancy has adequately decreased during the past two minutes. The last test distinguishes an incident from a bottleneck by indicating that a reduction in downstream occupancy has occurred over a short period of time as a result of the incident (3).

The FRESIM (12) model is selected in this study for data acquisition through simulation because of its accuracy, wide acceptability and option provided for modeling a variety of traffic incidents. FRESIM is a traffic simulation program developed by Federal Highway Administration (FHWA). Training of neural network model requires large amount of data. The collection of such a large incident data set from real traffic situation, is a difficult and tedious task. In this paper, therefore, an attempt is also made to investigate the relationship between the size of the training data set and effectiveness of training. Finally, the paper concludes the strengths and weaknesses of the developed neural model along with direction for future work.

FRESIM Calibration

The data collected for the calibration of FRESIM simulation model comprise of flow and speed data from a section (6.1 km) of Second Stage Expressway, Bangkok. The configuration of the expressway section used in this study is shown in Figure 1.

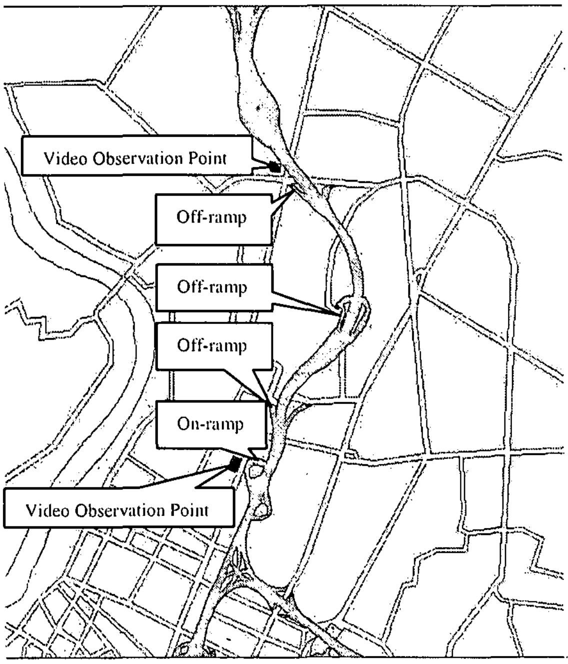

Figure 1 Study Section, Second Stage Expressway

The FRESIM model was calibrated using flow and speed data observed from the field and by comparing them with the values obtained from simulation. Separate calibration was carried out for peak and off-peak periods.

FRESIM can generate vehicle entry headway non-stochastically or stochastically using either a normal or an Erlang distribution. The form of the Erlang distribution is as follows:

$$f(t) = \frac{(qa)^a t^{a-1} e^{-aqt}}{(a-1)!} \quad \text{where, a=1,2,......} \tag{2}$$

Where, "t" is headway and "q" is the average traffic volume per lane. The parameter, a, describes the level of randomness of the distribution ranging from a=1 (most random) i.e. exponential distribution to $a=\infty$ (complete uniformity). For calibration of FRESIM model all the four headway distribution options available in the model were tried with different free flow speed values with the objective of minimizing the following normalized error function.

$$J = \frac{1}{N}\sum_{i=1}^{N}\left\{\left[\frac{q_{oi}-q_{si}}{\sigma_{of}}\right]^2 + \left[\frac{v_{oi}-v_{si}}{\sigma_{ov}}\right]^2\right\} \tag{3}$$

where,

q_{oi}= Flow observed at ith minute in the field,

q_{si}= Flow obtained at ith minute from simulation,

v_{oi}= Speed at ith minute observed from field data,

v_{si}= Speed obtained at ith minute from simulation,

σ_{of}=Standard deviation of traffic flow observed from field,

σ_{ov}= Standard deviation of spot speed observed from field.

The calibration was done in a manner that one by one each headway distribution was adopted and a set of simulations were carried out with a range of free flow speed (88-112) kph. For each simulation run the normalized error function was calculated and the one that gave the least error was used in the data generation. For details, refer Riaz (13).

The summary of the calibrated parameters is as:

Peak Period

Headway distribution:	Uniform
Free flow speed:	108 kph

Off-peak Period:

Headway distribution:	Exponential
Free flow speed:	112 kph

The calibrated parameters are well justified, as during peak period the traffic is quite high forcing drivers to move at nearly a constant headway (safe stopping sight distance). For off-peak period, the traffic volume is low and the calibrated distribution is exponential. This again depicts the validity of the calibrated parameters, as exponential distribution is primarily known for its randomness.

FRESIM Validation

The model was validated for peak as well as off-peak periods using flow and speed data not used in calibration process. For validation purpose, simulation was carried out using calibrated parameters and traffic volume and speed data observed from field for every minute was compared with the corresponding simulated output. Statistical techniques were used for the evaluation of the validation of the model. Based on unequal variance t-test it was observed with 95% confidence that there was no significant difference in mean values of flow and speed for simulated and actual conditions for both peak and off-peak periods. The calibrated parameters were retained against default parameters and were used in simulating incident and incident free data. At the start of simulation, there are usually few vehicles in the network. Some time is needed so that the network attains the equilibrium state. Therefore, the initial output, the time till equilibrium was not attained was not used in the validation of the model to avoid any bias in the validation process.

The TRAF system employs a multiplicative, congruent technique to generate random numbers that are used to simulate the random elements of traffic flow. The base seed number affects decisions such as the routing pattern of each vehicle and the characteristics of the drivers and vehicles. When a new value of base seed number is assigned an entirely new traffic pattern is generated (12). To have confidence in simulation a number of runs by changing base seed number must be carried out and there should not be a drastic change in the output of the model. Simulation was repeated many times by changing the base random seed number and no drastic change was observed in the output.

Training Data Simulation

The calibrated FRESIM model was used for simulating incident and incident free data. Intuitively, incidents taking place on shoulders have a minimal effect on the road capacity and this hypothesis is also supported by FRESIM simulation. Such incidents were therefore not covered in this study.

For training and searching the optimum neural network configuration, total 1500 data sets including incident and incident free states under varying traffic conditions ranging from peak- to off-peak flow were simulated. The details of simulated data are as follows. At present as there are no detectors installed on the expressway, a 500 meter detector spacing was assumed. The study section was divided into total ten segments. First fifty incidents were assigned to each segment. The longitudinal position of an incident in a segment was randomly selected.

One/Two lane blockages:

25 incidents / segment = 25*10 = 250 incidents

250 incidents, both peak and off-peak period, 2*250=500

Incident free data:

Incident free input vectors = 500

For a one-lane blockage case the blockage can be in any of the three lanes, the decision that which lane is blocked was decided randomly. Similarly, for a two lane blockage case, the blockage can be either 1st and 2nd lane or 2nd and 3rd lane. This blockage pattern was also decided randomly.

Training Data Characteristics

Figures 2, 3, 4 and 5, show the typical transition from incident free to incident state for one- and two lane blockage incidents, respectively. The transition from incident free to incident state causes sudden fluctuations in traffic flow followed by change in pattern of spot speed and density. Figure 2 and 3, show that there are minor differences between upstream and downstream detectors before incident is activated. After incident is activated there is a sudden increase in the spot speed difference between the two detectors causing a steep drop that can be seen in figure 2.

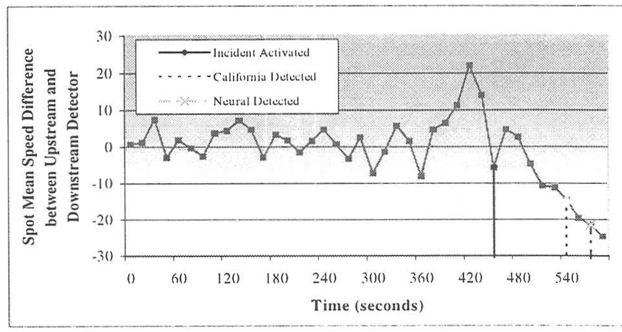

Figure 2 Spot Speed Trend during One-Lane Incident

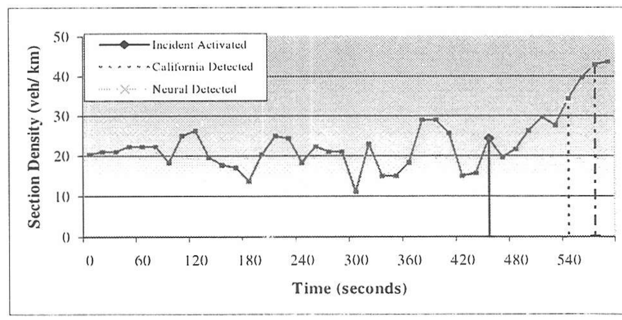

Figure 3 Density Trend During One-Lane Incident

The drop in figure 4 is steeper because of higher severity of two-lane blockage incident. The analogous phenomenon of sudden increase in density after incident activation can be observed in figures 3 and 5.

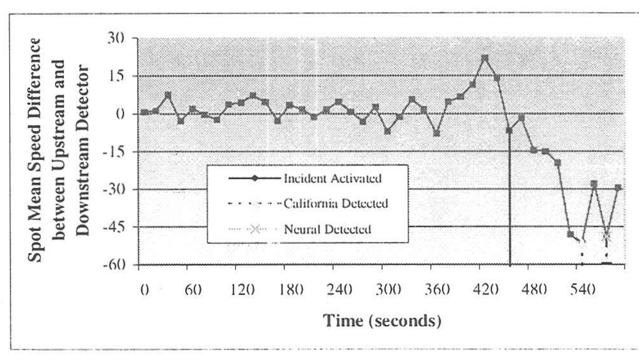

Figure 4 Spot Speed Trend during Two Lane Incident

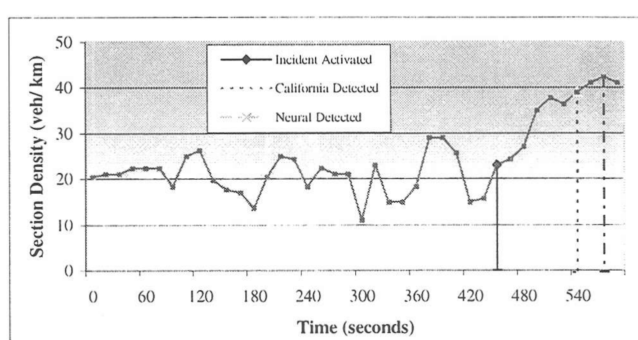

Figure 5 Density Trend During Two Lane Incident

Test Data Simulation

The trained network must be tested in order to evaluate the measure of effectiveness of training. Different researchers have varying opinion about the size of the test data set, but most of them agree on a ratio of 80:20 between training and test data set (14). For testing of the trained neural network, the first thing needed was the test data set comprising incidents under a variety of traffic conditions. Again, the FRESIM model that was earlier used for simulating data for training neural model under different incident conditions was used for generation of test data. A variety of incidents consisting of different lane closure patterns and location along the section were simulated in FRESIM for the generation of test data set. The test data set in this study comprised of 1000 input vectors, much bigger if compared to 0.2*1500 = 300 (20% of the size of the training data set) than the size as recommended by different researchers. Out of total 1000, there were 600 (60%) incident free input vectors and 400 (40%) input vectors under incident conditions. The split between one lane- and two-lane blockage incidents were 50:50 (200 under each category). A large size like this gives more confidence to the training of the neural network model. For the generation of test data set, many simulation runs were carried out with different traffic flow volume and random seed numbers. The neural model performance was evaluated on the basis of detection rate (DR), false alarm rate (FAR) and time to detect (TTD).

Neural Network Model

Artificial neural networks take their name from the networks of nerve cells in human brain. The neuron is the basic processor in neural networks. Neurons are connected to each other by synaptic weights. Neural network models are trained to adjust the weights so that application of a set of inputs produces a desired set of outputs. Back propagation paradigm is a very powerful paradigm commonly used for training of neural model and is also employed here. For more details on neural networks and back propagation, refer to Wasserman (15) and Dayhoff (16).

Neural Model Formulation

Input Layer

It is customary for the number of nodes in the input layer to be equal to the number of independent variables in the study. It is not necessary that the higher the number of neurons in the input layer the better will be the neural network performance. In search of optimum parameters to be used as input to neural network model, hundreds of training sessions were carried out using training data simulated earlier. A brief summary of the search for input variables to neural model is shown in Table 1. Input variables of set no.6, performed the best among all the data sets tried. In this data set, scaling or normalization technique as proposed by Garson (14) was used. All the input values, densities and difference between speeds, were divided by an arbitrary number 100. The training after normalization resulted in an improved network that was fairly closed to the one desired for this study. This input configuration was retained and had been later used for extensive search of other neural model parameters.

Table 1 Different Input Data Combination Sets

Set	*Upstream Detector*	*Downstream Detector*	*Section*
1	Flow, Speed & Occupancy	Flow, Speed & Occupancy	Density
2	Flow, Speed & Occupancy	Flow, Speed & Occupancy	-
3	Flow & Speed	Flow & Speed	Occupancy
4	Speed	Speed	Density
5	Difference between upstream & downstream detectors speed		Density
6	Same as Set no. 5, but input vectors were normalized		
7	Same as Set no. 6, except that for speed absolute difference was used		

Output Layer

Since the data generated consist of three traffic situations incident free, one and two lane blockage incidents. The number of neurons in the output layer can vary form one to three. Only one neuron is needed if it is desired to classify the incident or incident free state, say with output less than 0.5 mapped as incident free and output greater than 0.5 to 1, mapped as incident condition (irrespective of one or two lane blockage).

The optimum number of neurons in the output layer was again determined on a basis of trial and error procedure. The number of neurons in the output layer was varied from one to three and for each selection, the number of neurons in the hidden layer was varied from 7 to 20. Total 42 training sessions were carried out (14 for each output case) and the number of iterations for each session was limited to 150 as the network attained fair level of stability after 150 iterations. The network that resulted in lowest sum of Root Mean Square error had 15 neurons in the hidden layer and two neurons in the output layer while the number of neurons in the input layer were set to 24 for all three cases. The output signals used for mapping incident free state were

(0,0) and for incident state were (1, 1). This network was selected for further analysis.

Hidden Layers

As with most neural modeling decisions, trial and error is necessary to determine the optimum number of neurons in the hidden layer. In this research, the network with one hidden layer and fifteen neurons in it performed the best. The final network configuration of input, hidden and output layers is shown in Figure 6. In the figure, all interconnections between layers are not shown for the sake of clarity.

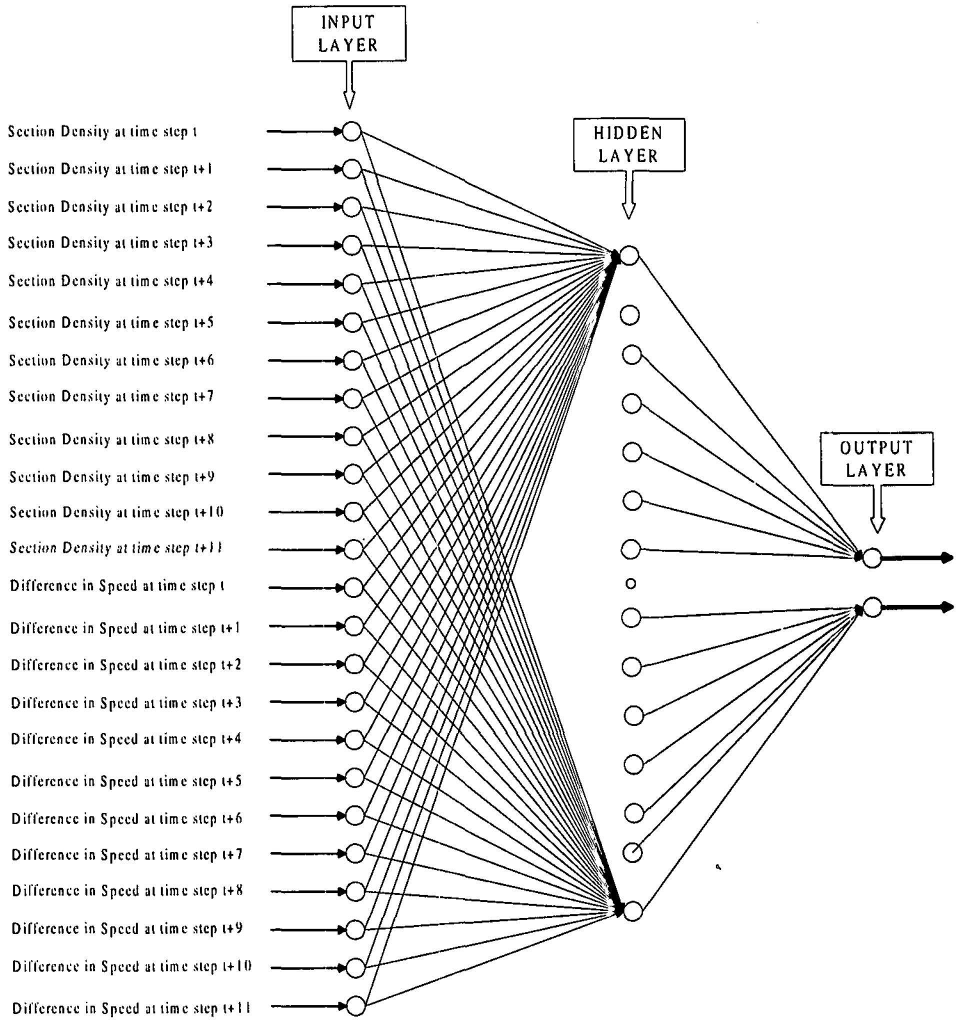

Figure 6 Optimum Network Configuration

Neural Model Evaluation

Detection Rate (DR)

Detection rate is the number of incidents detected divided by the total number of incidents. The detection rate was determined by applying test data set to the trained neural model. The test data set contained total four hundred (400) incidents including both one- and two-lane blockage. FRESIM model has the capability of evaluating the measure of effectiveness of California, Payne and Double Exponential algorithms. These algorithms were compared among each other based on default parameters as suggested by FRESIM manual and the best one found among them i.e. California algorithm was compared with the neural network model. The overall performance of neural network model was found superior to California algorithm. California algorithm performed marginally better to neural network algorithm in the detection of two lane blockage incidents. The comparative performance evaluation is shown in Figure 7.

The incident patterns that passed undetected through neural network model were incidents simulated under low traffic conditions. Detection rate for two lane blockage incidents was found superior to that of one-lane blockage incidents. This is in consistent with the fact that two lane blockage incidents have much more severe impacts on traffic conditions as compared to one-lane blockage incidents.

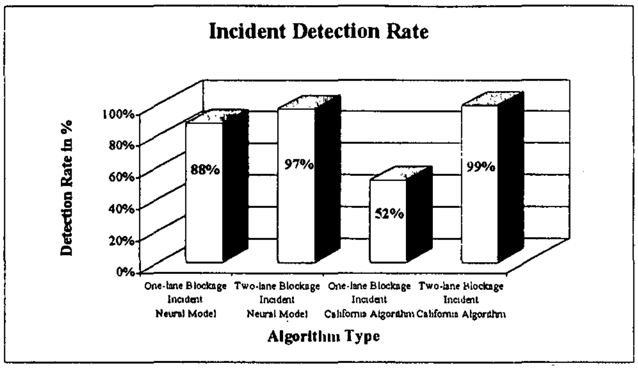

Figure 7 Detection Rate Comparison

False Alarm Rate (FAR)

False alarm rate is the number of incident detection made by algorithm when there is actually no incident to number of algorithm applications. In order to evaluate FAR, the neural network model was tested with six hundred (600) incident free patterns under varying traffic conditions. The neural network model successfully identified 581 out of 600 incident free patterns whereas it failed to identify 3% of incident free patterns and wrongly classified them as patterns under incident conditions. For California algorithm the percentage of incorrect classification was found to be 9%. Most of the incident free patterns wrongly classified were those simulated under heavy flow conditions. Although from theoretical point of view, the performance of the neural network model deemed quite satisfactory it still needs further improvement before practical application of the algorithm.

Time to Detect (TTD)

It is time from start of incident to the time it is detected by the algorithm. The average time to detect an incident is shown in Figure 8.

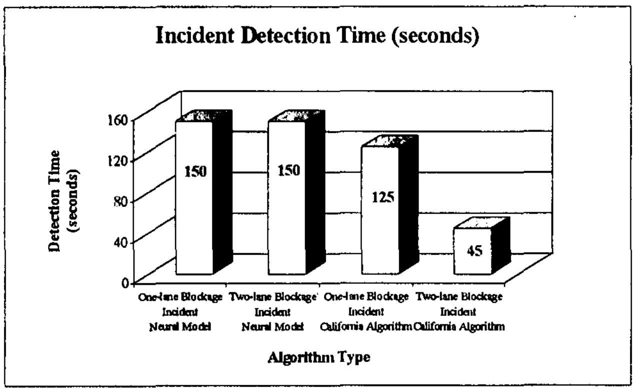

Figure 8 Average Incident Detection Time

Since neural network model used input data spanned over twelve time steps, they have a longer detection time as compared to conventional algorithm.

Data Size and Neural Model Performance

The effectiveness of a large data size for training of neural model cannot be overemphasized. Considering the difficulties involved in acquiring actual traffic data during incidents, the improvement in the performance of neural model with the increase in data size is investigated. The neural model was trained one by one by data sets of sizes 750, 900, 1200, 1500, derived from training data set, and the performance of the neural model was evaluated on the basis of DR, FAR and TTD. The performance of neural network model with change in data size is shown in Figure 9.

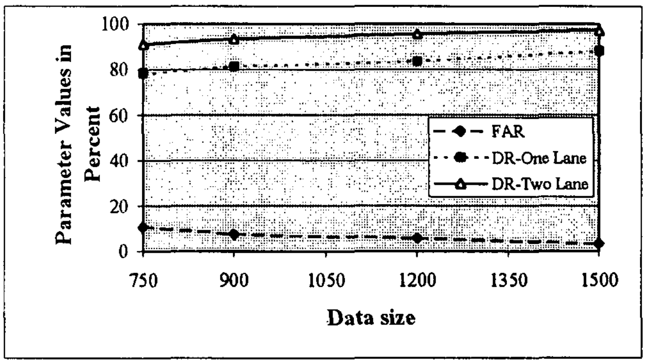

Figure 9 Neural model Performance at Different Data Size

The graph depicts that there is an improvement in the performance of neural model with the increase in the size of the data set. Although the improvement in performance seems slow but it is substantial. The finding supports the positive impact of a large data set on the performance of the neural model and establishes some basic interrelationship between data size and improvement in the performance of the model.

Pros and Cons

Neural network model performance was found superior to California algorithm for detection of incident free conditions and specially one lane blockage incidents, whereas California algorithm performed marginally better to neural network algorithm in the detection of two lane blockage incidents.

During a one-lane blockage incident, 1/3rd reduction in capacity takes place for a three-lane freeway facility. The remaining 2/3rd capacity is good enough for traffic volume to pass through without much hindrance during low traffic flow conditions. Therefore, some one-lane blockage incidents especially during low traffic volume remained undetected. During a two-lane blockage incident on a three-lane facility, there is a 2/3rd reduction in capacity takes place. Therefore, unless the traffic volume is very low there is definitely a sudden significant change in traffic pattern that takes place compared to incident free states. Because of this notable impact neural network model as well as the California algorithm successfully classified most of the two lane incident patterns correctly.

Sometimes at on- and off-ramps because of merging and diverging traffic, there are large variations in spot speed with a simultaneous increase in section density even during incident free states. The performance of neural model under such conditions may be improved either by adding a persistence test or by training separate neural model for on- and off-ramps. The persistent test may improve the performance of the neural network model in terms of FAR but it will also result in deterioration in terms of DR. A careful and detailed analysis, therefore, is needed to search the best combination of FAR and DR. The addition of persistence test is left for further study. If separate neural models are trained for on- and off-ramps they may have more tolerance for short-term traffic fluctuations but again at the cost of detection rate. In this study, only one neural model was trained for both intermediate freeway sections and on- and off-ramp sections.

Summary and Recommendations

In this study, a neural network model is trained by back propagation using density and spot mean speed traffic data to differentiate incident and incident free states. The performance of the neural network model is compared with conventional California algorithm and is found superior. The effect of data size on the performance of the neural model is also investigated. Neural network models have advantage over conventional algorithms because of their ability to incorporate errors or imperfect inputs and can give meaningful outputs with high accuracy. Therefore, incident detection is found significantly better for neural model as compared to conventional algorithms. Future work will focus on evaluation of the algorithm based on actual traffic data under incident and incident free conditions.

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