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INCIDENT DETECTION ALGORITHM BASED ON NEURAL NETWORK MODEL AND MACROSCOPIC SIMULATION CONTINUITY EQUATION*

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1. Background

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 algorithms developed are based on comparison of traffic flow parameters like developed 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. In an attempt to reduce the false alarm rate Levin and Krause [3] incorporated the historical probability distribution and proposed to use Bayes rule. Dudek and Messer [4] 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 [5] on the basis of data collected from surveillance centers developed an auto-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.[6] 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.

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. Neural networks 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 [7] 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 blocking during freeway incidents using neural networks. Different types of neural network 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, primarily responsible for false alarms, this study integrated neural network model with continuity equation of macroscopic traffic simulation model.

The continuity equation is capable of reflecting different traffic states with reasonable accuracy, as density is a unique traffic flow parameter. The continuity equation is used for the estimation of density in this study. The continuity equation is,

$$k_j^{n+1} = k_j^n + \frac{\Delta t}{\Delta x_j}\left[q_{j-1}^n - q_j^n + r_{in} - r_{Out}\right] \tag{1}$$

The study used traffic data spanned over twelve time steps in continuity. The time step size used is fifteen seconds. The continuity in data captured the inherent random fluctuations in traffic and therefore reduced the false alarms because of short-term traffic fluctuations.

At present detector data are not available in Bangkok. Also, the training of neural network model requires large data set. The collection of such a large data set from real traffic situation, is a difficult and tedious task. In this paper, therefore, the FRESIM model is selected in this study for data generation. An attempt is also made to investigate the relationship between the size of the training data and effectiveness of training.

2. 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 technique commonly used for training of neural model and is employed here. For more details on neural networks and back propagation, refer to Wasserman [9] and Dayhoff [10].

3. FRESIM Calibration

The data collected for the calibration of FRESIM [11] model comprise of flow and speed data collected from a section (6.1 km) of Second Stage Expressway, Bangkok. The FRESIM model was calibrated for peak and off-peak period using observed flow and speed data. Different headway distribution options available in FRESIM model were tried one by one along with a combination of free flow speed values to minimize the following objective function.

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

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.

Uniform headway distribution with a free flow speed of 108 kph gave minimum error for peak period, whereas for off-peak period exponential distribution with a free flow speed of 112 kph minimized the objective function.

4. FRESIM Validation

The FRESIM model was validated for peak and off-peak period using other observed data set. The validation was carried out by t-test with a 95% confidence interval and it was found that there was no significant difference in the mean values of flow and speed for simulated and actual conditions. Moreover, in FRESIM driver and vehicle characteristics are modeled by the base seed number. Simulation was repeated many times by changing the base random seed number and no drastic change was observed in the output.

5. 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 neural network, total 1500 data sets including incident and incident free states under varying traffic conditions ranging from peak-to off-peak flow were simulated. 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, 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 is again based on the random numbers. 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 using random numbers.

6. Neural Model Formulation

(1) Input Layer

The number of neurons in the input layer are usually equal to the number of inputs but which data should be used for optimal performance is a trial and error procedure. In search of optimum input to neural network model, hundreds of training sessions were carried out using different input parameters combinations and network performance was evaluated by comparing the output from the network and the desired output. 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 [12] 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.

(2) 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 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.

(3) 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 1. In the figure, all nodes and interconnections between layers are not shown for the sake of clarity.

7. Incident Data Patterns 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. Figure 2 and 4, show that after incident is activated there is a sudden increase in the spot speed difference between two adjacent detectors causing a steep drop and can be seen in figures. The drop in figure 4 is steeper because of higher severity of two-lane blockage incident. The analogous phenomenon of increase in section density can be observed in figures 3 and 5.

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		

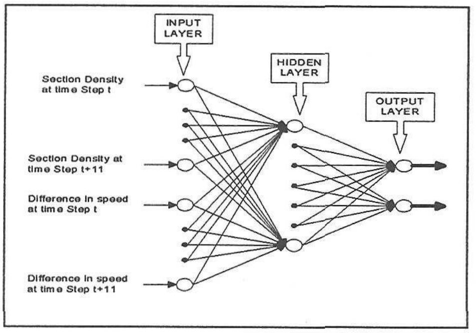

Figure 1 Optimum Network Configuration

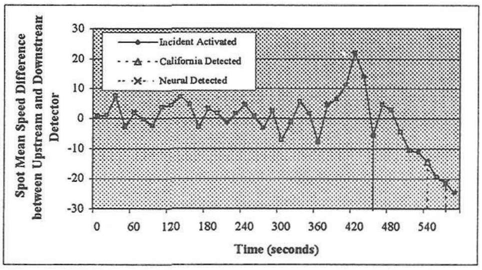

Figure 2 Spot Speed Trend during One-Lane blockage Incident

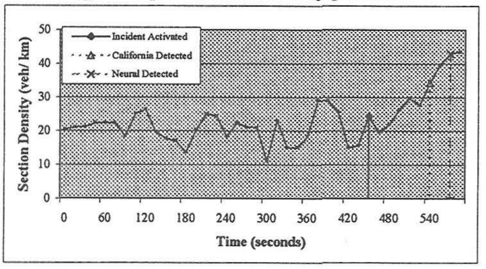

Figure 3 Density Trend during One-Lane blockage Incident

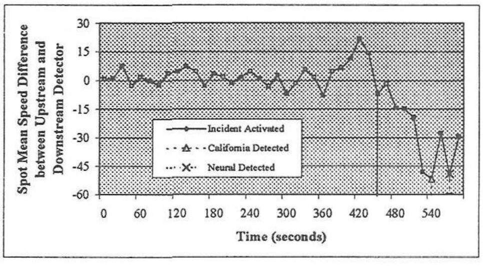

Figure 4 Spot Speed Trend during Two-Lane blockage Incident

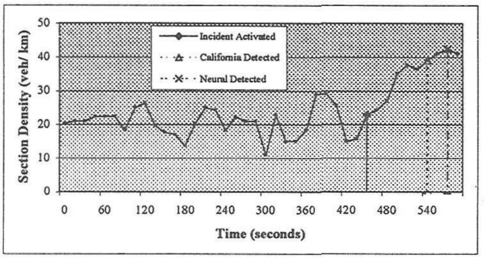

Figure 5 Density Trend during Two-Lane blockage Incident

8. Test Data Set

The test data set in this study comprised of 1000 input vectors, out of which, there were 600 (60%) incident free input vectors and 400 (40%) input vectors under incident conditions including both one- and two-lane blockage. The split between one and two-lane blockage incidents were 50:50 (200 under each category). For the generation of test data set, many simulation runs were carried out with different traffic flow volume and random seed numbers. The evaluation was primarily based on the detection rate (DR), false alarm rate (FAR) and time to detect (TTD).

9. Neural Model Evaluation

(1) Detection Rate (DR)

Detection rate is the number of incidents detected divided by the total number of incidents. 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 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 6.

(2) 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. Most of the incident free patterns not correctly identified were those simulated under heavy flow conditions. Neural network model was found to have difficult time in the correct classification of such patterns. For California algorithm, the percentage of incorrect classification was found to be 9%. 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.

(3) Time to Detect (TTD)

It is time from start of incident to the time it is detected by the algorithm. The average detection time for both one- and two-lane blockage incidents for neural model is 150 seconds. California algorithm took 125 seconds an average to detect one-lane blockage incident and 45 seconds an average to detect a two-lane blockage incident. Since neural network model used input data spanned over twelve time steps, they have a longer detection time as compared to conventional algorithm.

10. Data Size and Neural Model Performance

Considering the difficulties involved in acquiring actual traffic data during incidents, the performance of neural model is investigated with data sets of size 750, 900, 1200 and 1500. The performance was evaluated on the basis of DR, FAR and TTD and is shown in Figure 7. 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.

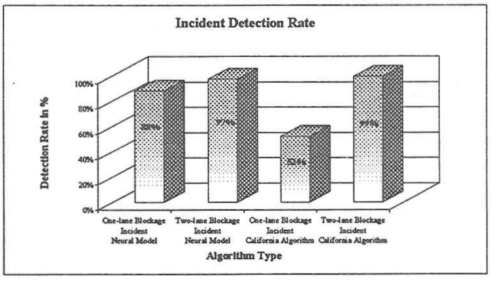

Figure 6 Detection Rate Comparison

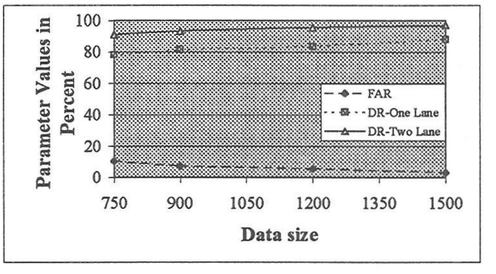

Figure 7 Neural model Performance at Different Data Size

11. 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 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 detector data under incident and incident free conditions.

References

1. Payne, H.J. and Tignor, S.C. Freeway incident-detection algorithms based on decision trees with states. Transportation Research Record, Washington, D.C., USA, 682, 1978, pp.: 30-37.
2. Levin, M. and Krause, G.M. Incident detection algorithms. Transportation Research Record, Washington, D.C., USA, 722, 1978, pp.: 49-64.
3. Levin, M. and Krause, G.M. Incident detection: A Bayesian Approach. Transportation Research Record, Washington, D.C., USA, 682, 1978, pp.: 52-58.
4. Dudek, C.L. and Messer, C.J. Incident detection on urban freeways. Transportation Research Record, Washington, D.C., USA, 495, 1974, pp.: 12-24.
5. Ahmed, S.R. and Cook, A.R. Application of time series analysis techniques to freeway incident detection. Transportation Research Record, Washington, D.C., USA, 841, 1982, pp.: 19-21.
6. Balke, K., Dudek, C.L. and Mountain, C.E. Using probe-measured travel times to detect major freeway incidents in Houston, Texas. Transportation Research Record, Washington, D.C., USA, 1554, 1996, pp.: 213-220.
7. Stephanedes, Y.J. and Liu, X. Artificial neural networks for freeway incident detection. Transportation Research Record, Washington, D.C., USA, 1494, 1995, pp.: 91-97.
8. Cheu, R.L., Recker, W.W., and Ritchie, S.G. Automated detection of lane blocking freeway incidents using artificial neural networks. Transportation Research Part C, Vol.3, No.6, 1995, pp.: 371-388.
9. Wasserman, P.D. Neural Computing Theory and Practice, Van Nostrand Reinhold, Newyork, 1989.
10. Dayhoff, J. Neural Network Architecture. Van Nostrand Reinhold, 1990.
11. Traffic Software Integrated System, Version 4.2, User's Guide. Federal Highway Administration (FHWA), USA, March 1998.
12. Garson, G.D. An Introduction Guide for Social Scientists. SAGE Publications, London, 1998.