CHAPTER 8 CONCLUSIONS

This chapter summarizes the major findings of the current research. Some general conclusions are described based on the discussion of previous chapters in section 8.1 and section 8.2 shows the possible directions for further works.

8.1 General Conclusions

1. Summary of literature review

Early incident detection algorithms focused on pattern comparison methods using raw traffic data gathered by loop detectors. Recently, various advanced techniques, such as artificial intelligent based algorithms, fuzzy logic, fuzzy expert systems, genetic algorithms, and image processing technologies, have been proposed and tested to achieve real-time and more precise incident detection. However, most incident detection algorithms may have encountered one or some of the following issues:

- The detection performance is subject to the algorithm thresholds, traffic flow conditions, and the distance between two adjacent detectors. Most detection algorithms are not transferable in that parameters and thresholds of an algorithm must be recalibrated and revalidated to be valid for different locations or times. Notice that these algorithms are strong site-related.

- Quantity and quality of traffic flow data are subject to detector types. Flow parameters collected by loop detectors, for instance, are often limited with lower accuracy. In addition, it is difficult to reflect the section-related traffic flow behavior only depending on spot traffic parameters obtained from loop detectors.

- Most algorithms only focus on detecting whether there is an incident without further identifying the location or severity of an incident. Because of the difficulty in gathering actual incident data, most algorithms adopt off-line validation with simulation data or incident database.

2. Data for validation

It is very difficult to generate sufficient real traffic incidents to validate AID algorithms. Thus, this research adopts off-line validations by simulation. The Paramics, which calibrated by a deliberate real incident case, is employed to produce the simulated incidents and incident-free data under different scenarios. All simulation runs are divided into two parts:

- Thirty-second traffic flow data are collected in 45 minutes at the same site where the deliberate incident was experimented. The data cover a typical afternoon peak hours is used for the input traffic data of Paramics.

- Thirty-second traffic flow data are collected from 6:00 to 12:00, which including a typical morning peak hours and two off-peak periods before and after that peak, at the same site. The flow data variations for six hours, in which conspicuous fluctuations and manifest changes in traffic volume (from low to intermediate to heavy volumes and then from heavy to intermediate to low volumes) are found. Such drastic variations are utilized to inspect the performance of proposed approaches under different traffic conditions.

3. FNN approach

- Conventional traffic incident detection algorithms usually subjectively set the parameters and use crisp criteria in distinguishing the incident-occurrence from incident-free, thus may result in poor detection performance as the traffic conditions alter drastically. Neural network (NN) approaches have the advantages of learning capability to avoid subjectively setting of the parameters and possessing high fault tolerance due to the distributed memory of parameters separately stored on each link of the network. However, the crisp criteria for judging the incident occurrence used in NN approaches may lead to misjudgment due to too sensitive to the crisp criteria. If incorporating fuzzy system and fuzzy inference into the NN (called FNN), we can avoid the problem of too sensitive to the crisp criteria but still possess self-learning capability with high fault tolerance.

- The off-line tests based on 45-minute simulation condition have shown that the proposed FNN approach has reached an average detection rate as high as 89.50% while keeping the average false alarm rate as low as 0.068%, and average time to detection as short as 78 seconds under the 30-second detection time interval situation, which including two-lane and three-lane mainline section. Based on 60-second detection time interval, the average detection rate is 88.57%, the average false alarm rate is 0.057%, and the average time to detection is 153 seconds. However, the FNN approach has different detecting performance under different incident scenarios. The statistics tests show that the interval of detecting time has significant influence on time to detection, but the influence on detection rate and false alarm rate is unremarkable. It implies that incident detecting capability of FNN approach is not affected by the length of interval of detecting time (30 or 60 seconds). In addition, the detection rate and time to detection of the FNN approach are also affected by incident location. The incidents, which take place in the inner lane, are easier and faster to be detected than which occur in the outer lane. The nearer (from either upstream or downstream) the distance is the easier to be detected. Consequently, the statistics tests indicate that the performance of FNN approach is affected by the density of detectors deployed.

- When changing the network structure of FNN approach from upstream and downstream detectors to single downstream detector, it will cause the detection rate to fall and the false alarm rate to rise. It is mainly due to that the detection rate is affected by the distance between incident location and detector. Reducing the amount of input parameters will gradually deteriorate the performance of detection rate and false alarm rate, but the scale is slightly. The results imply that FNN approach has high tolerance and stability when the input traffic data is not fully collected due to detector malfunction, so that it has practical implement.

4. RTFNN approach

- However, their FNN approach did not adaptively adjust the network parameters in response to the prevailing traffic conditions, hence there may have some room for the improvement. A rolling-trained fuzzy neural network (RTFNN) approach for freeway incident detection is developed to capture the change in traffic dynamics through the network training. The main advantage of our proposed RTFNN approach is to adaptively adjust the network parameters using the most up-to-date traffic data in response to the prevailing traffic conditions so as to improve the detection performance over the conventional FNN approach.

- Our numerical example based on the 6-hour simulation tests has shown that the proposed RTFNN approach has reached an average detection rate as high as 93.95% while keeping the average false alarm rate as low as 0.075%. Without rolling-trained, in contrast, the average detection rate for the same FNN structure is 91.09%. The results have also shown that as the traffic volumes vary from low to high and then change from high to low, the detection performance for RTFNN is getting better and better, but not for the FNN approach, strongly suggesting that our proposed RTFNN approach is capable of adaptively adjusting the network parameters in response to the traffic variations.

- The sensitivity analyses have found that, compared with the base condition (rolling interval = 60 minutes and training size = 120 samples), short or long rolling intervals will downgrade the detection performance due mainly to insufficient up-to-date training samples collected for short rolling intervals and incapable of capturing the traffic flow variations for long rolling intervals. Similarly, small training sample sizes will also downgrade the detection performance due to difficulty in reaching the convergence of total error function. In this two-lane freeway case study, we have found that the highest detection performance is at a rolling horizon interval of 45 minutes and a training size of 90 samples.

5. Chaotic diagnosis approach

- Our philosophy of chaotic diagnosis for traffic incidents is to use the change in appropriate chaotic parameters to examine the existence of an incident. This research examines the changes in chaotic parameters including largest Lyapunov exponent, capacity dimension, correlation dimension, relative Lz complexity, Kolmogorov entropy, delay time, and Hurst exponent to develop the abnormality diagnosis for incidents. Tests for chaos show that the traffic flow dynamic time series have the nature of deterministic chaos.

- In the preliminary examination for chaos, the largest Lyapunov exponent and delay time are found that they have changed significantly before and after the experimented incident. In order to detect the occurrence of an incident shortly, the largest Lyapunov exponent is chosen as the chaotic parameter for chaotic diagnosis.

When largest Lyapunov exponent value is greater than 0.49, the traffic flow is identified as normal (no incident occurs); if it is less than 0.49, the traffic flow is viewed as abnormal (an incident occurs).

- Under the condition of 6-hour simulation tests, which covering the various traffic dynamic, the overall average detection rate of chaotic diagnosis approach based on Lyapunov exponent chaotic parameter is 95.99%, which is slightly better than that by the most conventional incident detection algorithms based on microscopic or macroscopic traffic parameters. However, the false alarm rates (the average false alarm rate is 1.8017%) are a bit too high. It requires further investigation.

6. Comparison results

- In sum, the enhancement of detection rate (and time to detection) without significantly deteriorating the false alarm rate and the superior performance of RTFNN over FNN should be ascribed to the rolling-trained effects of adaptively adjusting the network parameters in response to the traffic variations.

- The chaotic diagnosis approach keeps the higher detection rate than the RTFNN approach. It is found that the chaotic diagnosis approach has slightly higher false alarm rate and both of detection rate and false alarm rate have statistical significant difference at 5% significance level. Thus, the chaotic diagnosis approach improves the detection rate, but it also accomplishes the deterioration of the false alarm rate. The average time to detection requires only about two time steps for RTFNN and the fixed three time steps for the chaotic diagnosis approach. Even though the chaotic diagnosis approach has better detection rate, which related to RTFNN approach, but the higher false alarm rate and fixed time to detection make the chaotic diagnosis approach is inferior then RTFNN approach in practical implement.

- Overall, the off-line test results have indicated the feasibility of achieving the real-time automatic incident detection using the proposed fuzzy-neural-based approaches and chaotic diagnosis approach. The FNN/RTFNN approaches have lower false alarm rate and lower time to detection. The performance of FNN/RTFNN approaches depends on distance between the detectors. Notice that the performance of RTFNN is not affected by the various traffic flow conditions. The chaotic diagnosis approach, which can identify the incident and incident-free characteristics, has higher detection rate and fix time to detection, but the performance heavily depend on subjectively setting thresholds.

8.2 Future Extensions

1. Improvement of FNN/RTFNN approaches

- Our findings are based on some thirty-six incident scenarios in the two-lane freeway contexts. We can further examine the robustness of RTFNN approach at different places (e.g., three- or four-lane freeway mainline sections) with different scenarios (e.g., incidents at different locations and affecting more than one lane). Development of new methods to determine the optimal rolling horizon interval and optimal training size deserves further exploration.

- The supervised learning rules used in the proposed FNN/RTFNN approaches could be changed into unsupervised or associate learning rules to examine the performance of training process. Furthermore, the training sample data set could be expanded by keeping the incident data (regardless of the different traffic dynamics) and replacing the incident-free data to only focus on the variation of normal traffic condition in rolling-trained procedure.

2. Improvement of chaotic diagnosis approaches

- Note that the largest Lyapunov exponent threshold value of 0.49 might only valid for our specific traffic demand pattern. Different threshold values might be anticipated if the traffic demand varies. More scenarios including incidents taking place at different locations with various distances from the downstream detector on various numbers of lanes of freeway need to be analyzed before a generalized conclusion can be made. To enhance the detection rate and reduce the false alarm rate, altering the threshold values, attempting other chaotic parameters or using the data gathered by two adjacent detectors also requires further studies.

3. Future applications

- The proposed approaches merely indicate the existence of incident. The lane-based FNN structure may be re-established to offer additional incident related information such as incident location, number of lanes blocked due to incidents, or duration of incidents.

- Further studies may combine of fuzzy-neural-based and chaotic-based approaches to develop the hybrid incident detection algorithm. The hybrid algorithm with chaotic-based approach, which has the capability of identification, for initial diagnosis and with fuzzy-neural-based, which has the capability of classification, for confirmation of incidents may have the potential advantages for incident detection.