CHAPTER 7 RESULTS OF CHAOTIC DIAGNOSIS

This chapter proposes a new approach for traffic incident detection -- chaotic abnormal traffic diagnosis. The underlying theory for this new approach is to measure the change in chaotic traffic parameters, including largest Lyapunov exponent, correlation dimension, relative Lz complexity, correlation time, and Hurst exponent, to examine the existence of traffic incidents. First, the examination for the existence of chaos of the observed traffic flow time series data is described in section 7.1. Section 7.2 introduces the determination of threshold for incident detection and the off-line test results are shown as section 7.3. The comparison of incident detection performance between chaotic diagnosis and RTFNN is elaborated in section 7.4. Finally, section 7.5 presents a concise summary.

7.1 Examination for Chaos

As mentioned in section 4.1, under special permission from the Freeway Authority, we intentionally generate a real traffic incident by stalling two cars, lasting for 15 minutes in site, to block the outer lane and the shoulder in the northbound two-lane mainline section of Taiwan Freeway No. 1. Figure 7-1 compares the normal flow time series before this incident and the abnormal flow time series after the incident at the downstream camera site for consecutive 15 minutes. An insignificant change in the 30-second flow rate time series data in Figure 7-1 suggests that the change in downstream flow rate time series might not provide enough information for incident detection if we intend to apply the conventional traffic incident detection algorithms. For more details on this real incident experiment and testing for the difference of speeds or densities before and after the incident, please refer to section 4.1.

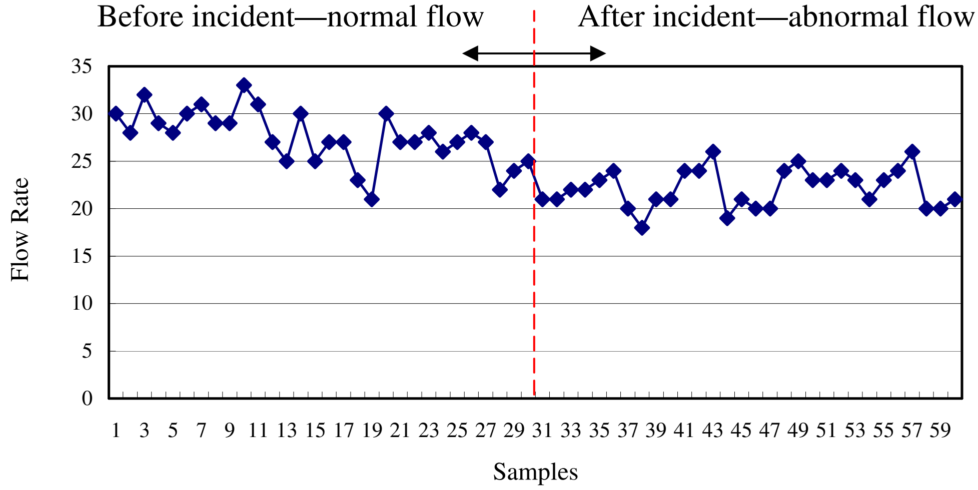


Figure 7-1 The 30-second flow rate time series at downstream

In general, the internal deterministic rules of a dynamic system cannot be confirmed only by a one-dimensional time series plots. But if we transform the system into another space (known as the phase space), we will probably find that although the system is aperiod on the time axis, there exists certain geometric order in the phase space. This process is called "phase space reconstruction." The process of phase space reconstruction will help understand the hidden deterministic rules for a dynamic system. Since the phase space retains essential properties of the original state space including the dimensionality, a phase space can be used not only to make short-term predictions but also to make a practical distinction between low-dimensional chaotic determinism and stochastic noise (Sugihara and May, 1990; Sugihara, *et al.* 1990).

The definition of chaos and its properties have been well established in the literature (for instance, Adrangi, *et al.* 2001; Barnett, *et al.* 1995; Hilborn, 1994; Kantz and Schreiber, 1997). A definition similar to the following is commonly found. The series a_t has a chaotic explanation if there exists a system (h, F, x_0) where $a_t = h(x_t)$, $x_{t+1} = F(x_t)$, x_0 is the initial condition at $t = 0$, and where h maps the *n*-dimensional phase space, R^n to R^1 and F maps R^n to R^n. It is also required that all trajectories x_t lie on an attractor A and nearby trajectories diverge so that the system never reaches equilibrium or even exactly repeats its path. For a chaotic time series, if one knows (h, F) and could measure x_t without error, one could forecast x_{t+i} and thus a_{t+i} perfectly. In order that F generates random-looking but in effect deterministic behavior, nearby trajectories must diverge exponentially and eventually fold back on themselves. The attractors may be thought of as a subset of the phase space towards which sufficiently close trajectories are asymptotically attracted.

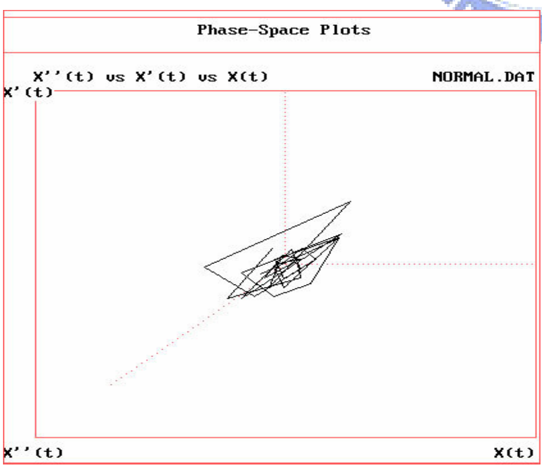
Use the concept of phase space reconstruction to convert one-dimensional flow rate time series into multi-dimensional phase space, in which traffic flows before and after the incident can be tested by various chaotic parameters. The analysis results are presented in Table 7-1. Note that Kolmogorov entropy is not reported in Table 7-1 due to insufficient samples.

Table 7-1 Chaotic parameters for 30-second flow rate time series

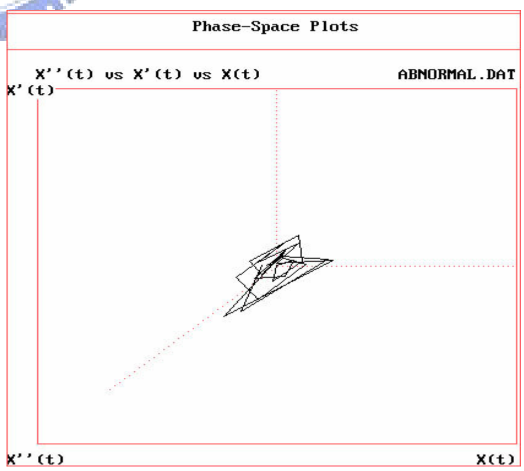
Chaotic Parameters	Before the incident (normal traffic)	After the incident (abnormal traffic)
Largest Lyapunov exponent	0.522	0.096
Capacity dimension	0.792	0.500
Correlation dimension	3	3
Relative Lz complexity	0.981	1.144
Kolmogorov entropy	N/A	N/A
Delay time	1.270	0.937
Hurst exponent	0.132	0.164
Conclusions	Chaos traffic	Period motion

It can be seen from Table 7-1 that largest Lyapunov exponent for the normal traffic flow (before the incident) is positive (=0.522), suggesting a deterministic chaos for the flow dynamics. For the abnormal traffic flow (after the incident), in contrast, largest Lyapunov exponent is near zero (=0.096), indicating a periodic motion for the flow dynamics. Note that the value of capacity dimension does not change much before (=0.792) and after (=0.500) the incident. Correlation dimensions before and after the incident are of the same (=3). The value of relative Lz complexity is 0.981 for the normal traffic flow, indicating a relatively complicated system; and it is 1.144 for the incident traffic flow, indicating a relatively simple system. The delay time for the normal traffic flow (=1.270) is larger than that for the incident traffic flow (=0.937). Hurst exponent does not change much before (=0.132) and after (=0.164) the incident. Based on the changes in these chaotic parameters, we conclude that traffic flow changes from relatively complicated chaotic dynamics (before the incident) to less complicated cyclic motions (after the incident).

Figure 7-2 demonstrates the three-dimensional phase space reconstruction for the 30-second flow dynamics before and after the incident. It can be noted that all the time paths in normal traffic condition (before the incident) seem to be attracted by a strange attractor. The nearby trajectories diverge exponentially and the locally diverging trajectories eventually fold back on themselves without repeating. Such an aperiodic motion is an important property for deterministic chaos. Note that all the time paths shrink to a smaller range in abnormal traffic condition (after the incident), implying that the flow time series after the incident is like a periodic motion.



(a) before the incident

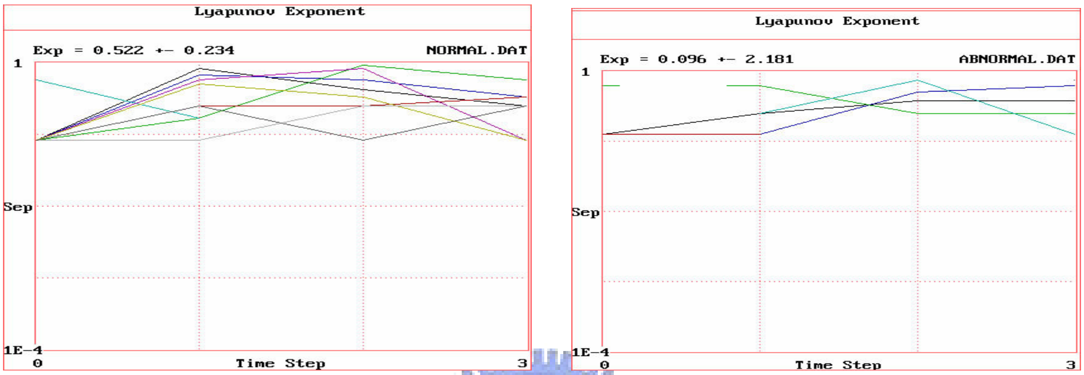


(b) after the incident

Figure 7-2 Phase space reconstruction for the 30-second flow rate time series

In order to identify the significant chaotic parameters, we further plot the changes in these parameters before and after the incident. Figure 7-3 illustrates the largest

Lyapunov exponent plots before and after the incident (with embedding dimension of 1 and time step of 3). One can obviously see that the largest Lyapunov exponent in normal traffic flow condition is positive, indicating a deterministic chaotic dynamics; whereas it is close to zero in abnormal traffic flow condition, implying a periodic motion. Figures 7-4 through 7-7 present the plots of capacity dimensions, correlation dimensions, delay times, and Hurst exponents before and after the simulated incidents.

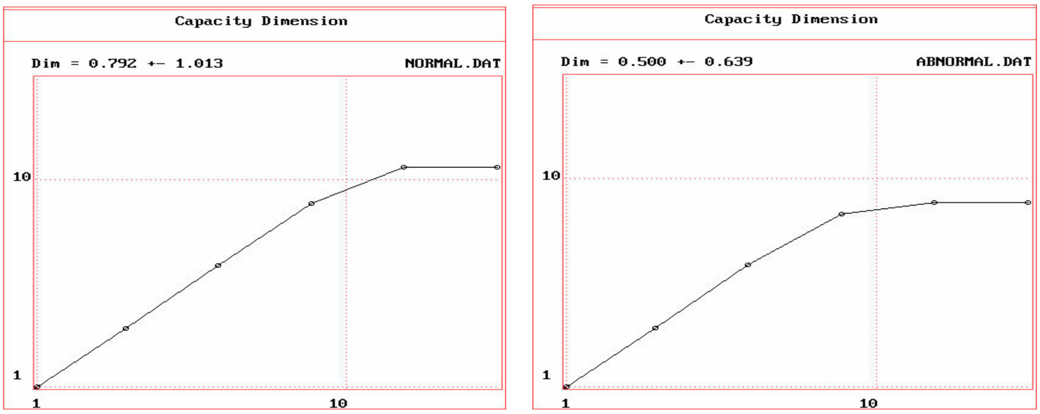


(a) before the incident (b) after the incident

Figure 7-3 Lyapunov exponent plots

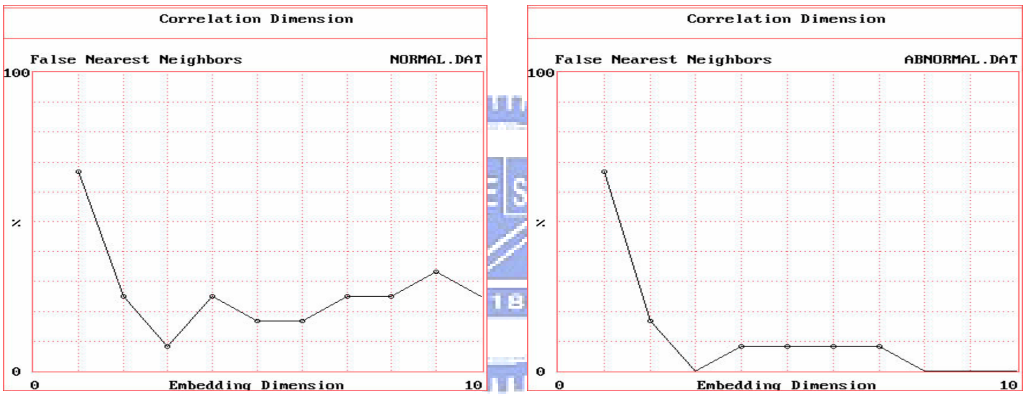
In Figure 7-4, the value of capacity dimension does not change much before and after the traffic incident. In Figure 7-5, false nearest-neighbors method is used to estimate the value of embedding dimension and it produces the same lowest value of embedding dimension for both normal and incident traffic flows. Figure 7-6 indicates that the delay time in normal traffic flow condition is decreasing progressively with an indication of chaotic dynamics, while in incident traffic flow condition it presents a quasi-periodic movement. In Figure 7-7, Hurst exponent does not change much before and after the traffic incident. From the above plots, it can also be concluded that the characteristics of traffic flow convert from chaotic dynamics (before the incident) to periodic motion (after the incident).

From the above analysis and plots, the chaotic parameters that change remarkably before and after the traffic incident are largest Lyapunov exponent and delay time. This paper uses the largest Lyapunov exponent for abnormality diagnosis because we find that the time needed for the change in delay time is much longer than that needed in the Lyapunov exponent.



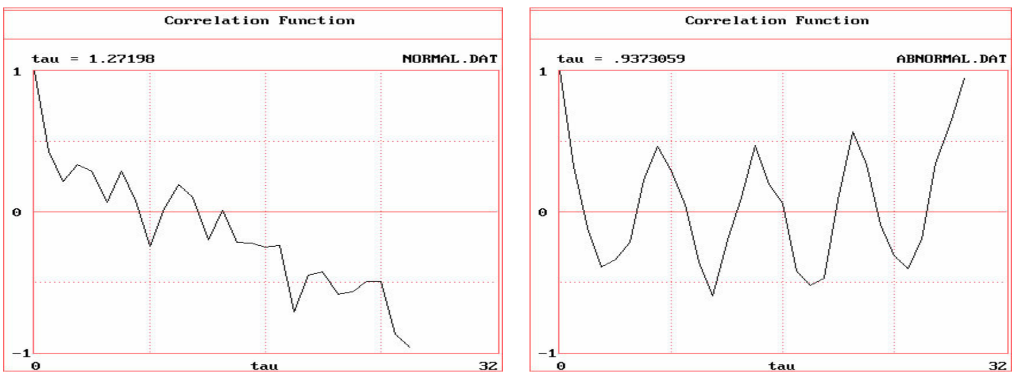
(a) before the incident (b) after the incident

Figure 7-4 Capacity dimension plots



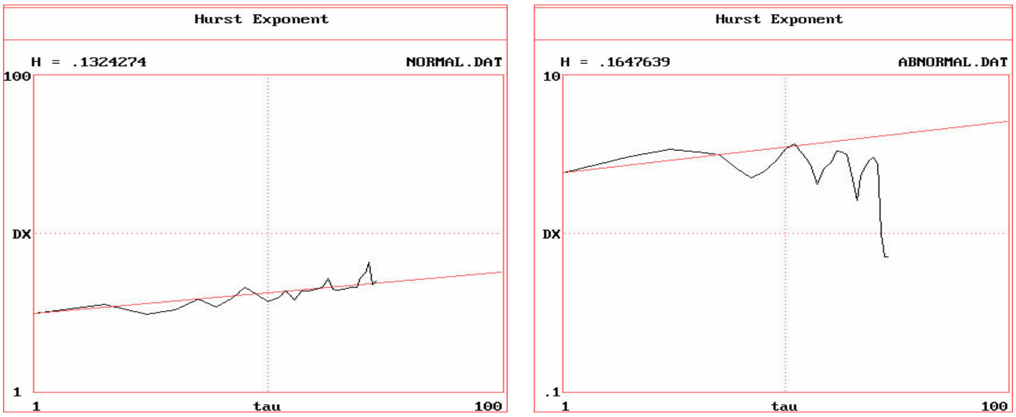
(a) before the incident (b) after the incident

Figure 7-5 Correlation dimension plots



(a) before the incident (b) after the incident

Figure 7-6 Delay time plots



(a) before the incident (b) after the incident

Figure 7-7 Hurst exponent plots

7.2 Determination of threshold for λ_{max}

In order to determine the threshold value for the largest Lyapunov exponent, we use the calibrated simulator – Paramics to simulate different incident scenarios. The scenarios are composed of incidents taking place at different locations (inner or outer lane) with various distances (250, 500, 750 meters) from the downstream detector on a two-lane freeway mainline. Thirty times of simulation runs are carried out in each scenario case. The ranges of changes in largest Lyapunov exponents before and after the incident are reported in Table 7-2. From this table, the values of largest Lyapunov exponent in normal traffic flow range from 0.347 to 0.861. An “interval search algorithm” is further employed to obtain the near optimum threshold value and we find that the best diagnosis accuracy is achieved at largest Lyapunov exponent equal to 0.49. Therefore, we use this threshold value for the off-line tests.

$$\lambda = \begin{cases} \geq 0.49 & \text{Normal Traffic (incident-free)} \\ < 0.49 & \text{Abnormal Traffic (incident-detected)} \end{cases} \qquad (7\text{-}1)$$

The simulation results from Table 7-2 also show that before the incident, all the largest Lyapunov exponent values are positive (representing a chaotic dynamics) and after the incident, all the largest Lyapunov exponent values are negative or near zero (indicating a cyclic movement). Once again, these results agree with the real incident analysis results -- traffic flow changes from relatively complicated chaos (before the incident) to less complicated cycle (after the incident).

7.3 Off-line Test Results

In the following off-line tests, if the largest Lyapunov exponent value is greater than 0.49, the traffic flow will be identified as normal (no incident occurs). By contrast, if the largest Lyapunov exponent value is less than 0.49, the traffic flow will be identified as abnormal (an incident occurs). In order to evaluate the detection performance by the chaotic parameters, we conduct off-line tests by using the calibrated Paramics again to simulate different incident scenarios. Ninety-six simulation runs are carried out in each scenario case. To evaluate the detection performance, detection rate (DR) and false alarm rate (FAR) are used and defined as
follow.

Table 7-2 also reports the detection performance. We find that the overall average DR is 93.75% and FAR is 2.60%. The best DR is 100% where the incident takes place in the outer lane 250 meters from the downstream detector; while the worst DR is 87.5% for the scenario case that the incident occurs in the inner lane 500 meters from the downstream detector. The detection rates diagnosed by the largest Lyapunov exponent are slightly better than those accomplished by most of conventional incident detection algorithms with DR near 90% (Lan and Huang, 2003). However, the false alarm rates are a bit too high. It could be due to too sensitive of the largest Lyapunov exponent.

Table 7-2 Changes in Largest Lyapunov Exponents and Detection Performance

Location of incident	Distance from downstream detector (meters)	Largest Lyapunov exponent[1]		Detection performance[2]	
		Before incident	After incident	Detection rate (DR)	False alarm rate (FAR)
Inner lane	250	0.490~0.714	-1.136~0.478	93.75 %	0.00 %
	500	0.455~0.778	-0.838~0.618	87.50 %	3.12 %
	750	0.502~0.861	-0.797~0.656	93.75 %	3.12 %
Outer lane	250	0.588~0.822	-1.258~0.513	100.00 %	3.12 %
	500	0.347~0.848	-0.622~0.639	93.75 %	3.12 %
	750	0.540~0.742	-0.808~0.539	93.75 %	3.12 %
Overall average				93.75 %	2.60%

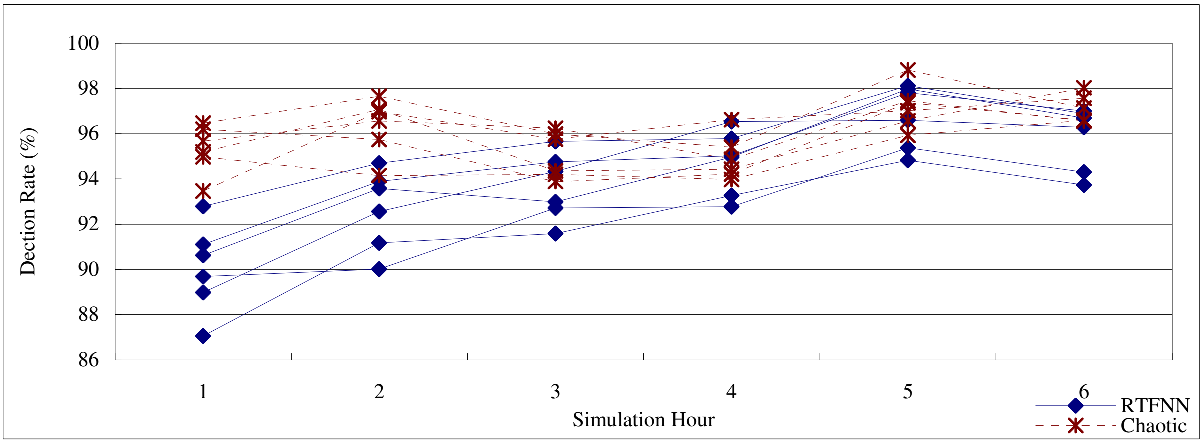
1. 30 simulation runs for each incident scenario case

2. 96 simulation runs for each incident scenario case

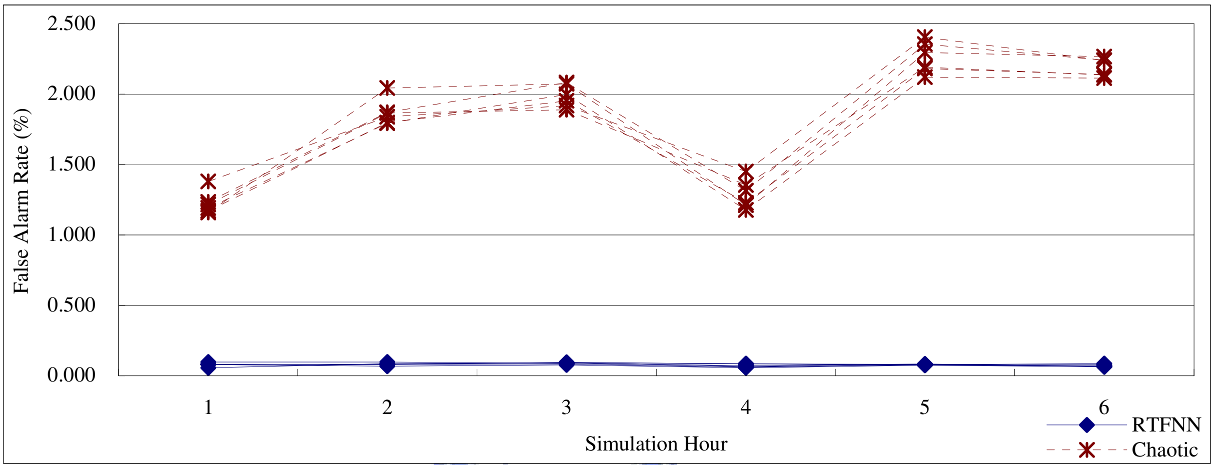
7.4 Comparison with RTFNN

Base on the 30-seconds traffic flow data are observed from 6:00 to 12:00 covering a typical morning peak hours and two off-peak periods before and after that peak at the experimented site, the off-line tests comparison between RTFNN (the rolling horizon is 60 minutes and the training sample size is 120 samples) and chaotic diagnosis is established.

Figure 7-8 reveals that the chaotic diagnosis approach has outperformed with higher DR, compared with the RTFNN approach in various traffic conditions. But the chaotic diagnosis approach has accompanied with inferior FAR. Note that the six points in the Figure 7-8 represent six different incident locations within the same simulation hours. Figure 7-9 further presents the interaction between DR and FAR for both approaches.



(a) DR



(b) FAR

Figure 7-8 Comparison of detection performance for each simulation hour between RTFNN and chaotic diagnosis approaches

(rolling horizon = 60 minutes, training sample size = 120)

Table 7-3 reports the statistical difference of mean values (t-test) of detection performance between these two approaches. As time goes by, RTFNN gradually outperforms because RTFNN updates the trained parameters in every 60 minutes, however, the chaotic diagnosis approach keeps the higher DR. It is found that the overall DR for RTFNN is 93.95% and for the chaotic diagnosis approach is 95.99%; both are quite high and have statistical difference at 5% significance level. The overall FAR for RTFNN is 0.0754% and for the chaotic diagnosis approach is 1.8017%; the chaotic diagnosis approach has slightly higher and both have statistical significant difference. The overall TTD requires only about two time steps, 68.39 seconds for RTFNN and the fixed three time steps for the chaotic diagnosis approach.

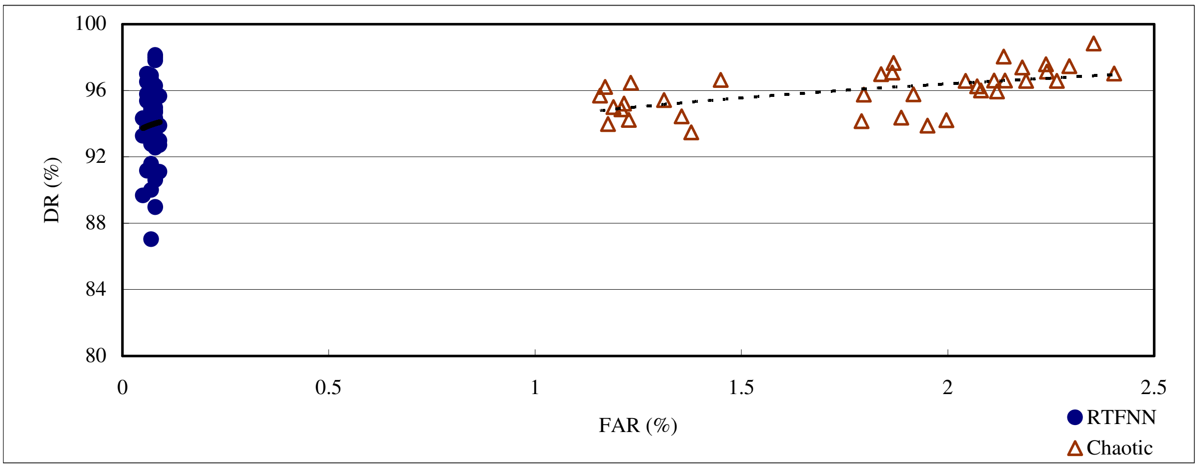


Figure 7-9 Graph of detection rate vs. false alarm rate between RTFNN and chaotic diagnosis approaches for 36 incident scenarios

Table 7-3 Test for the difference of detection performance between RTFNN and chaotic diagnosis approaches (rolling horizon = 60 minutes, training sample size = 120)

Simulation hour (time of day)	Hourly volume (vph)	Detection approaches	DR Average[1]	DR Test result[2]	FAR Average[1]	FAR Test result[2]
1 (6:00-7:00)	2,403	RTFNN	90.04%	SD (0.021)	0.0794%	SD (0.003)
		Chaotic	95.33%		1.2243%	
2 (7:00-8:00)	2,919	RTFNN	92.65%	SD (0.022)	0.0815%	SD (0.002)
		Chaotic	96.36%		1.8676%	
3 (8:00-9:00)	3,664	RTFNN	93.67%	SD (0.021)	0.0881%	SD (0.001)
		Chaotic	95.07%		1.9841%	
4 (9:00-10:00)	4,514	RTFNN	94.72%	NSD (0.903)	0.0658%	SD (0.001)
		Chaotic	94.92%		1.2887%	
5 (10:00-11:00)	3,310	RTFNN	96.78%	NSD (0.615)	0.0742%	SD (0.003)
		Chaotic	97.19%		2.2570%	
6 (11:00-12:00)	2,484	RTFNN	95.82%	SD (0.037)	0.0634%	SD (0.002)
		Chaotic	97.08%		2.1884%	
Overall		RTFNN	93.95%	SD (0.013)	0.0754%	SD (0.002)
		Chaotic	95.99%		1.8017%	

Note: 1. Average represents the mean values of six incident scenarios, each of which undertakes 100 simulation runs.

2. NSD represents no significant difference and SD represents significant difference with P-value in parenthesis (α=0.05). The null hypothesis is that the mean values (DR or FAR) between two approaches are the same.

7.5 Summary

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 paper attempts 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.

We find that the chaotic parameters that change significantly before and after the experimented incident are largest Lyapunov exponent and delay time. In order to detect the occurrence of an incident shortly, we select the largest Lyapunov exponent as the chaotic parameter for abnormality 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). The overall average detection rate, which using 45-minute simulation off-line tests, based on Lyapunov exponent chaotic parameter is 93.75%, which is slightly better than that by the conventional incident detection algorithms (with an average detection rate of 90%) based on microscopic or macroscopic traffic parameters. However, the false alarm rates are a bit too high. It requires further investigation.

The high detection performance suggests that both RTFNN and the chaotic diagnosis approach approaches are all satisfactory in freeway incident detections; but the false alarm rate and detection time of the chaotic diagnosis approach could be significantly enhanced. Specifically, as the traffic conditions changed from low to high and then from high to low, the detection performance (DR and TTD) for RTFNN is increased from 90% to about 96%; but the detection performance for the chaotic diagnosis approach remains rather stable between 95% and 97%. As for the FAR, the overall performance shows that there is statistical significant difference between these two approaches (0.075% and 1.802%). In sum, the enhancement of DR significantly deteriorating the FAR due to too sensitive of the largest Lyapunov exponent and it maybe can reduce the FAR by adaptively replacing the thresholds.

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 or attempting other chaotic parameters also requires further studies.