Journal of the Eastern Asia Society for Transportation Studies, Vol. 6, pp. 1624 - 1636, 2005

TRAFFIC FLOW ANALYSIS WITH DIFFEERENT TIME SCALES

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Abstract: This paper examines the nonlinear dynamics of traffic time series data measured by different time scales, including one-minute, five-minute and ten-minute counts. The approach of Lan's *et al* (*Journal of the Eastern Asia Society for Transportation Studies*, Vol. 6, 2005) parsimony procedure is employed to test for chaos. The empirical results from the United States I-35 Freeway field data reveal that if the flow data are measured in one-minute, the traffic dynamics in the morning hours exhibit chaotic phenomena, However, if the same flow data are measured in five-minute and ten-minute, chaotic structures may disappear, and instead, quasi-periodic motions may emerge.

Keywords: chaos, parsimony procedure, quasi-periodic, short-term traffic flow

1. INTRODUCTION

Chaos is one type of behaviors exhibited in nonlinear dynamical systems. Some sudden and dramatic changes in nonlinear systems may give rise to the complex behavior called chaos. It is used to describe the time behavior of a system when that behavior is aperiodic (namely, trajectories or orbits never repeat) and is apparently noisy (looks like random) (e.g., Hilborn, 1994; Barnett, *et al* 1995; Adrangi, *et al* 2001; Sprott, 2003; Robinson, 2004). According to Sprott (2003), chaotic systems have several important features: (1) they are aperiodic; (2) they exhibit sensitive dependence on initial conditions (SDIC), hence they are unpredictable in the long run; (3) they are governed by one or more control parameters, a small change in which can cause the chaos to emerge or disappear; and (4) their governing equations are nonlinear. In addition, the geometry with non-integer dimensionality, called "fractal," also plays an essential role in chaotic systems. Due to the fractals, self-similarity (i.e., a portion of the system, suitably magnified, still looks like the system itself) is also an important feature for a chaotic system (Mandelbrot, 2000).

The word "chaos" was introduced by Li and Yorke (1975) to designate the nonlinear systems that have aperiodic behavior more complicated than equilibrium (fixed) points and periodic or quasi-periodic motions. In fact, a related concept of chaos -- the "strange attractor" was introduced earlier by Ruelle and Takens (1971) who emphasized more the complicated geometry of the attractor in phase space than the complicated nature of the motion itself. The theoretical works by these mathematicians supplied many of the ideas and approaches that were late applied in physics, celestial mechanics, chemistry, biology, and other fields. In traffic flow study, for instance, Disbro and Frame (1989) utilized chaos theory to describe the traffic flow phenomena. Dendrinos (1994), Iokibe, *et al* (1995), Frison and Abarbanel (1997), Zhang and Jarrett (1998) and Lan, *et al* (2003) also found that the short-term traffic flows have nonlinear chaotic phenomena. Addison and Low (1996, 1998) found that some specific parameter values of the GM car-following models exist in chaotic dynamics.

Whether there exist chaotic or random phenomena in the nature of traffic dynamics is still not generally clear. Only demonstrated with enough evidence can we utilize chaos theory to elucidate and predict the traffic flow dynamics and to further apply it for various purposes, including incident detection for non-recurrent congestion and traffic control for recurrent congestion. In order to gain deeper insights into the traffic flow dynamics and to look for effective indexes to distinguish chaos from randomness, Lan, *et al* (2005) attempted a battery of geometric plots and statistics to examine whether a traffic time series is chaotic or not. They found such indexes as largest Lyapunov exponent, power spectrum, and iterated function system (IFS) clumpiness map are most crucial indexes. Based on these three indexes, Lan, *et al* (2005) developed and verified a three-step parsimony procedure that could successfully identify if chaotic phenomena exhibit in traffic flow dynamics. Their empirical tests have shown strong evidence of chaotic structures, rather than stochastic structures, existent in one-minute traffic dynamics during the morning hours (6am to 9am) in the United States I-35 Freeway in Minneapolis, Minnesota. We wonder if chaotic features still exist in five-minute and ten-minute counts, if the same traffic data are examined.

The objective of this paper is to further scrutinize the nonlinear dynamics of traffic time series data measured by different time scales, including one-minute, five-minute and ten-minute counts. We would first convert the one-minute traffic data into five-minute and ten-minute counts, and then apply Lan's *et al* (2005) three-step parsimony procedure to examine the nonlinear dynamical properties. The paper is organized as follows. Section 2 highlights the parsimony procedure approach. Section 3 describes the empirical traffic flow data and their basic statistic properties. Section 4 conducts the testing for the traffic data measured by different time scales. Section 5 further verifies the findings by other geometric plots. Section 6 discusses the findings and proposes the extensions.

2. THE PARSIMONY PROCEDURE

Lan *et al* (2005) made use of many indexes (geometric plots and statistics) to compare the original and surrogate one-minute traffic time series data directly drawn from eight selected detector stations of the United States I-35 Freeway in Minneapolis, Minnesota. The geometric plots include state-space plots, return maps, phase-space plots, Poincare maps, iterated function systems (IFS) clumpiness maps, autocorrelation function plots, probability distributions, and power spectra. The statistics include largest Lyapunov exponent, Kolmogorov entropy, Hurst exponent, relative complexity, capacity dimension, embedding dimension, correlation dimension, and delay time. The most crucial and significant indexes that have obviously distinguished chaos from other nonlinear dynamical properties were selected to establish the three-step parsimony procedure. Details of the development of this proposed parsimony testing procedure can be referred to Lan's *et al* work on **identification for chaotic phenomena in short-term traffic flows: a parsimony procedure with surrogate data** (*Journal of the Eastern Asia Society for Transportation Studies*, Vol. 6, 2005). This paper only briefly narrates as follows:

Step 1. Examine the largest Lyapunov exponent (LE) for the original data

If the LE is negative, the time series will converge toward a stable sink (or called equilibrium fixed points in chaos literature). If the LE is zero, the time series is periodic in the sense that the trajectories will converge to a period-k sink (k is greater or equal to 2). If the LE is positive, the time series can be quasi-periodic, chaotic or stochastic, then we go to step 2.

Step 2. Examine the power spectrum of the original data

If the power spectrum is narrow and has only few (two or three) dominant sharp peaks, it must be quasi-periodic. In case that it is a broadband spectrum, it can be chaotic or stochastic, then we go further to step 3.

Step 3. Compare the IFS clumpiness between the original and surrogate data

If the IFS clumpiness map of the original data visually differs from the surrogates, then we have evidences (but not proof) that the time series is not stochastic (Smith 1992). In this case, we can probably say that the original time series exhibits chaotic structures.

Figure 1 depicts the concept of Lan's parsimony procedure. The first step can rule out the time series fixed points or periodic. The second step further rules out the possibility of quasi-periodic data. The final step is to make distinction between chaoticity and stochasticity once we already know that they are not fixed points, periodic, or quasi-periodic.

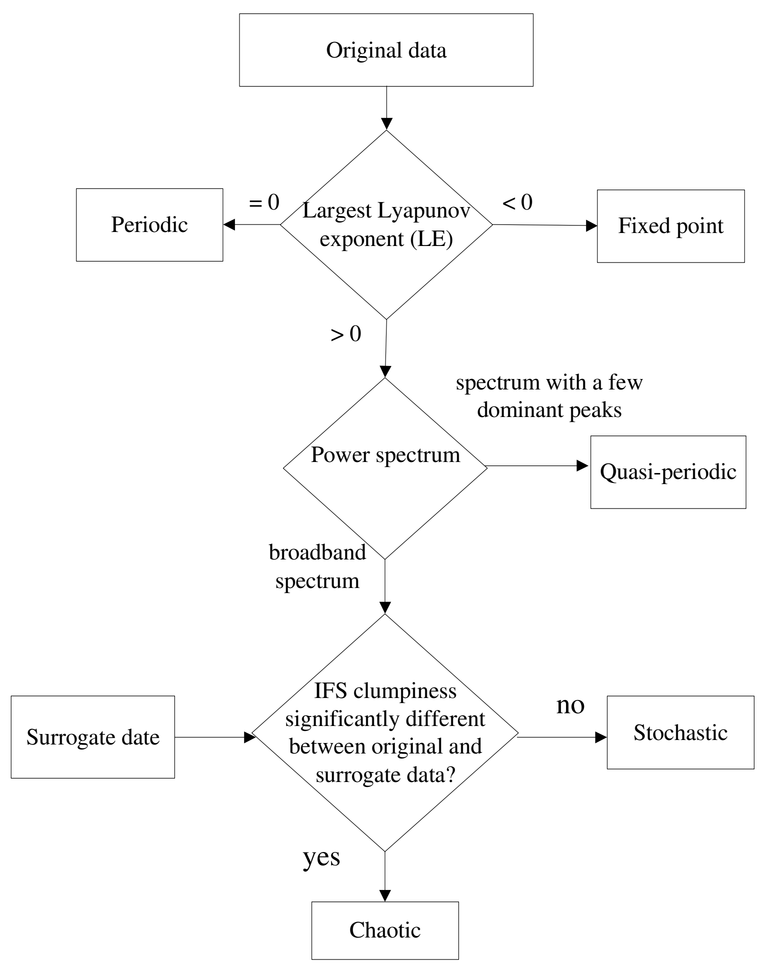
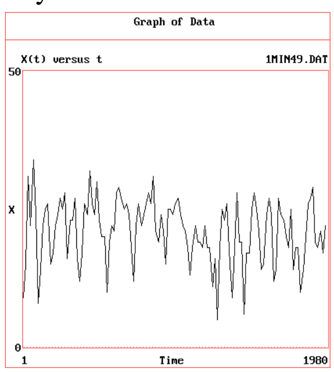


Figure 1. Lan's Parsimony Procedure
Source: Lan *et al* (2005)

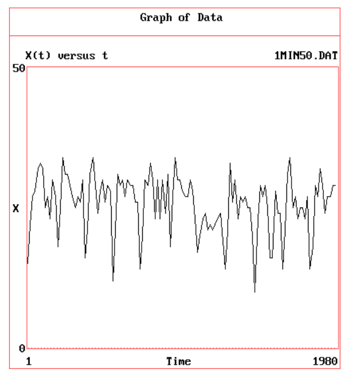
3. EMPIRICAL DATA

Our empirical traffic time series data are directly drawn from eight selected detector stations in the United States I-35 Freeway in Minneapolis, Minnesota. Averages of the lane-specific flow counts are accumulated over one-minute period for ten workdays' morning commuting hours from 6 am to 9 am each day. The average lane-flow rates for these eight stations range from 21.9 to 33.8 vehicles per minute, or equivalently, with average time headways from 2.74 seconds per vehicle (a moderately high flow) to 1.78 seconds per vehicle (a very high, near saturated, flow). We sum up the one-minute flows to convert into five-minute and ten-minute counts.

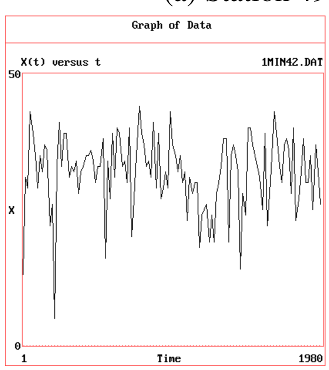
Figure 2 illustrates the one-minute traffic flow dynamics for four stations: 49 (lowest flow), 50 (intermediate flow), 42 (intermediate flow), and 55 (highest flow). Figures 3 and 4 further demonstrate the five-minute and ten-minute dynamics. Note from these three figures that the drastic fluctuations of one-minute flows have become less conspicuous as the time scale gets larger. It is mainly due to the "smooth out" effects by summing up the very oscillatory one-minute flow dynamics.



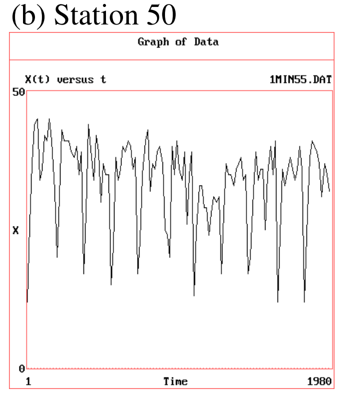
(a) Station 49



(b) Station 50

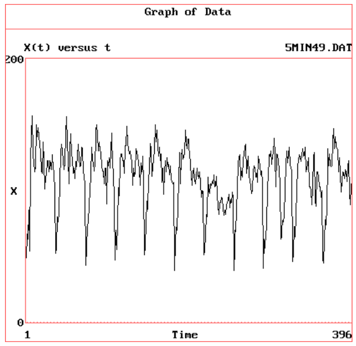


(c) Station 42

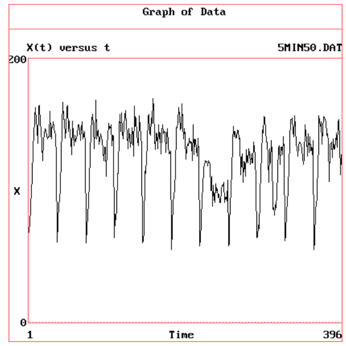


(d) Station 55

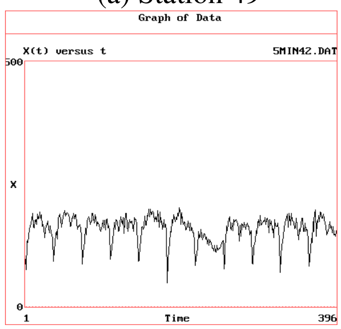
Figure 2. One-minute Traffic Flow Dynamics



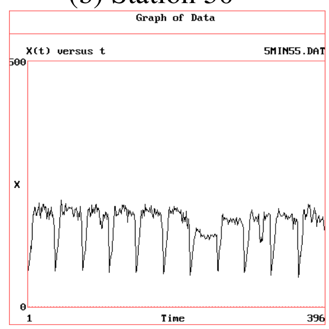
(a) Station 49



(b) Station 50

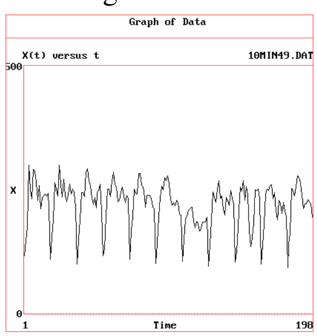


(c) Station 42

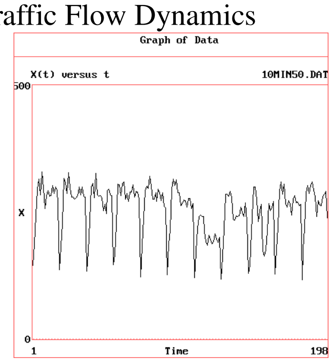


(d) Station 55

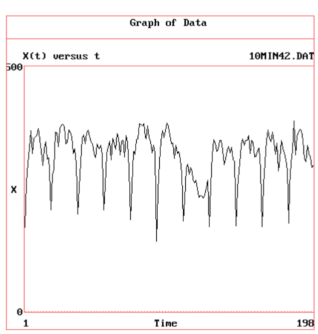
Figure 3. Five-minute Traffic Flow Dynamics



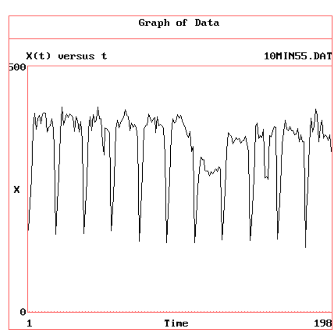
(a) Station 49



(b) Station 50



(c) Station 42



(d) Station 55

Figure 4. Ten-minute Traffic Flow Dynamics

Table 1 demonstrates the important descriptive statistics of these traffic data with different time scales for the selected four stations. The coefficient of variations of one-minute flow is greater than that of five-minute, which is greater that that of ten-minute. It also elucidates the fact that drastic fluctuations of shorter-term flow counts have become less conspicuous than the longer-term counts due to “smooth out” effect.

Table 1 also reports the symmetric property of the data distributions. The negative skewness represents the data structure characterized with high flow counts bunched close to the mean but low flow counts extend far from the mean for all stations with different time scales. We further examine if the data is normal distribution. Kurtosis far less than 3 represents all the data measured with different time scales are very flat-topped distributed.

Table 1. Statistic Properties for the Traffic Data Measures by Different Time Scales

Station No.	Properties	1-minute	5-minute	10-minute
42	Number of data points	1980	396	198
	Minimum value	0	48	144
	Average value	31.87	159.38	318.77
	Maximum value	48	201	389
	Standard deviation	6.435	25.43	48.69
	Skewness	-0.75	-1.238	-1.32
	Kurtosis	1.03	1.69	1.579
	Coefficient of variation	0.202	0.159	0.152
50	Number of data points	1980	396	198
	Minimum value	6	55	117
	Average value	25.59	127.98	255.97
	Maximum value	38	170	329
	Standard deviation	5.74	25.38	49.25
	Skewness	-0.73	-1.075	-1.16
	Kurtosis	0.18	0.462	0.569
	Coefficient of variation	0.224	0.198	0.192
49	Number of data points	1980	396	198
	Minimum value	5	39	92
	Average value	21.96	109.84	219.68
	Maximum value	36	157	300
	Standard deviation	5.67	23.44	44.86
	Skewness	-0.449	-0.96	-1.006
	Kurtosis	0.0276	0.597	0.646
	Coefficient of variation	0.258	0.213	0.204
55	Number of data points	1980	396	198
	Minimum value	9	60	131
	Average value	33.78	168.9	337.8
	Maximum value	48	218	418
	Standard deviation	7.63	35.35	69.45
	Skewness	-1.114	-1.378	-1.426
	Kurtosis	0.726	1.099	1.135
	Coefficient of variation	0.225	0.209	0.205

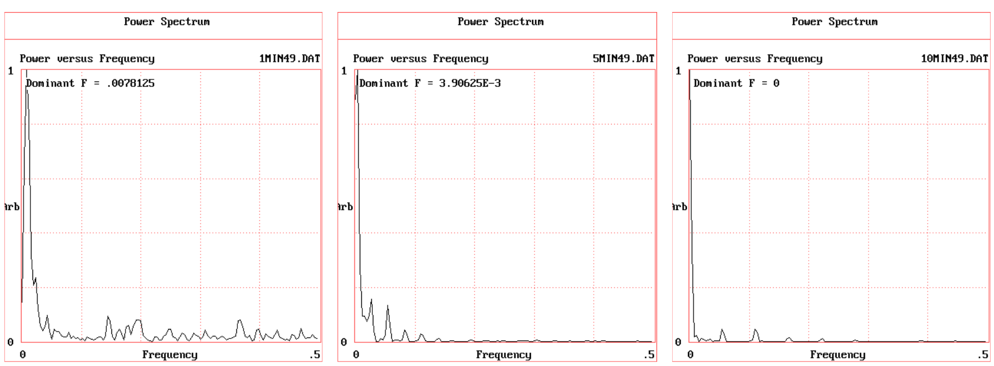
4. TEST FOR CHAOTIC DYNAMICS

We apply Lan's parsimony procedure to test the eight stations to see whether or not chaotic structures exhibit in one-minute, five-minute and ten-minute flow dynamics. The first step is to calculate the largest Lyapunov exponent (LE) and the results are presented in Table 2. Positive LE values for the original time series for all stations rule out the traffic dynamics with different time scales being fixed points or periodic. Therefore, we can proceed to step two.

Table 2. Largest Lyapunov Exponents

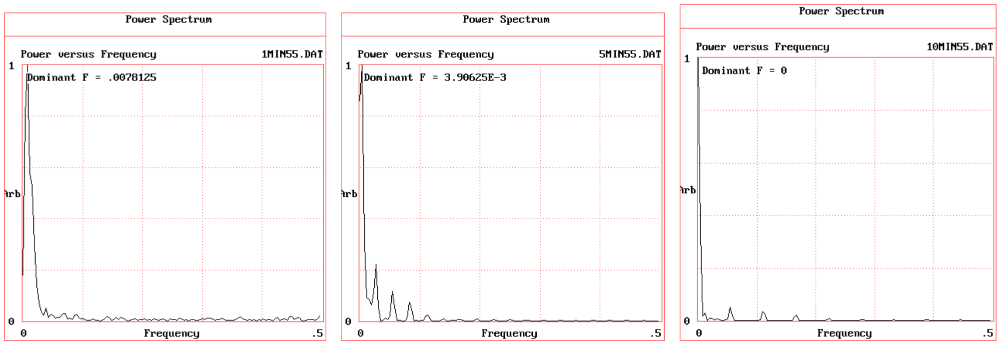
Station no.	Flow rates (veh/min-lane)	Traffic flow counts		
		1-minute	5-minute	10-minute
49	21.9	0.694	0.515	0.383
48	23.9	0.674	0.519	0.420
50	25.6	0.606	0.513	0.436
39	27.8	0.67	0.528	0.435
42	31.9	0.40	0.321	0.192
52	31.9	0.586	0.547	0.399
54	32.8	0.381	0.345	0.358
55	33.8	0.395	0.273	0.351

The second step is to look at the power spectra for the original time series data as presented in Figures 5 to 8. We find that only five-minute (Figures 5 (b), 6(b), 7 (b), and 8(b)) and ten-minute flow dynamics (Figures 5(c), 6(c), 7(c), and 8(c)) have spectra with few dominant peaks, which are evidence for quasi-periodic motions. Hence, we may conclude (but not prove) that the 5-minute and 10-minute time series data for the eight stations are more likely quasi-periodic motions. The one-minute flow data have shown broadband power spectra as in Figures 5(a), 6(a), 7(a), and 8(a), suggesting that the data could be stochastic or chaotic; therefore, we need to go to step three.



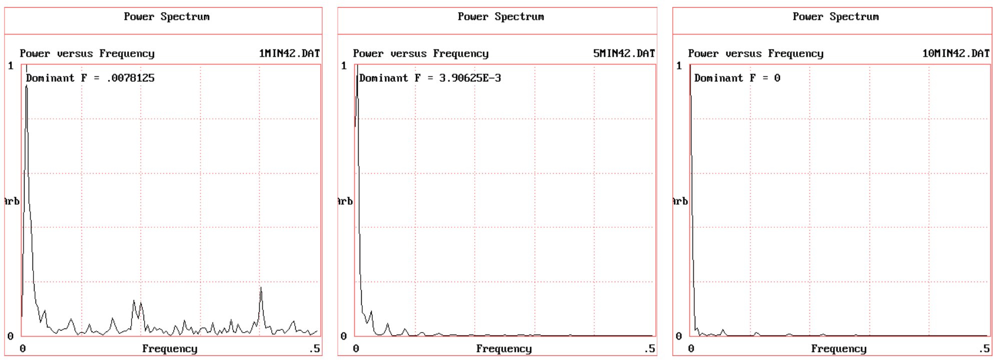
(a) One-minute (b) Five-minute (c) Ten-minute

Figure 5. Power Spectra (Station 49)



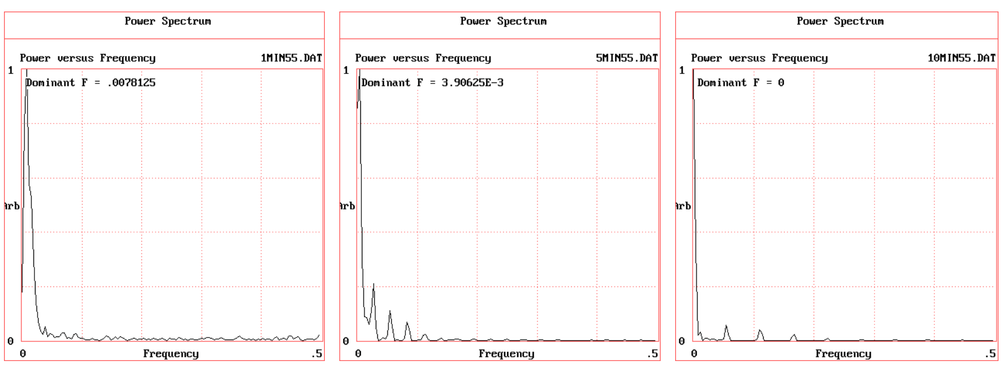
(a) One-minute (b) Five-minute (c) Ten-minute

Figure 6. Power Spectra (Station 50)



(a) One-minute (b) Five-minute (c) Ten-minute

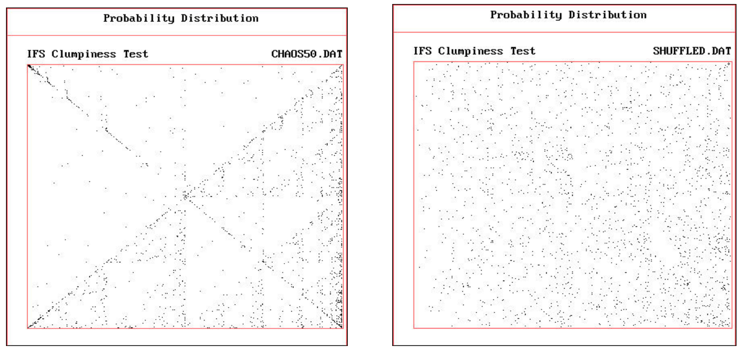
Figure 7. Power Spectra (Station 42)



(a) One-minute (b) Five-minute (c) Ten-minute

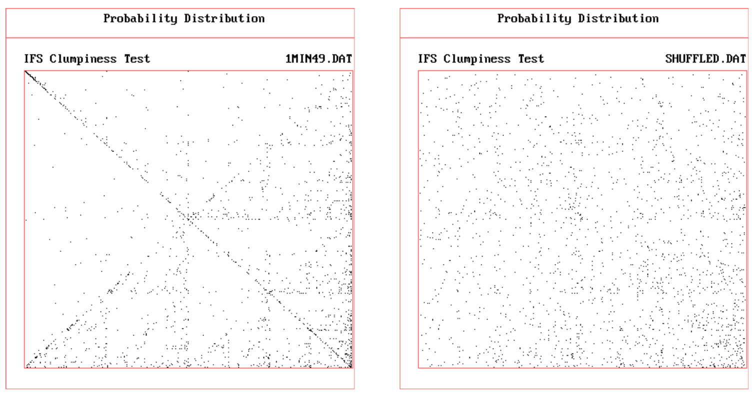
Figure 8. Power Spectra (Station 55)

The third step is to compare the IFS clumpiness maps between the original and surrogate data. Figures 9 to 12 demonstrate the IFS clumpiness maps of one-minute flows for stations 50, 49, 42, and 55. The IFS maps of one-minute traffic time series data at eight stations all reveal apparent difference between the original and surrogate data, which further rule out to be stochastic. As such, we may conclude (not prove) that all the one-minute flow dynamics for the eight stations exhibit chaotic dynamics.



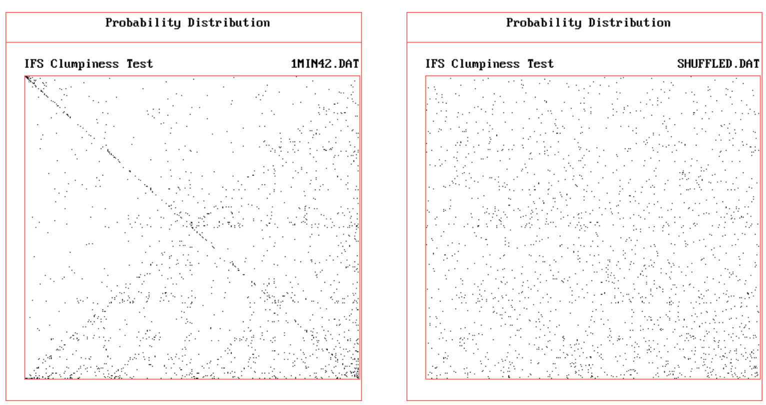
(a) Original data (b) Surrogate data

Figure 9. IFS clumpliness Maps for One-minute Flow (Station 50)



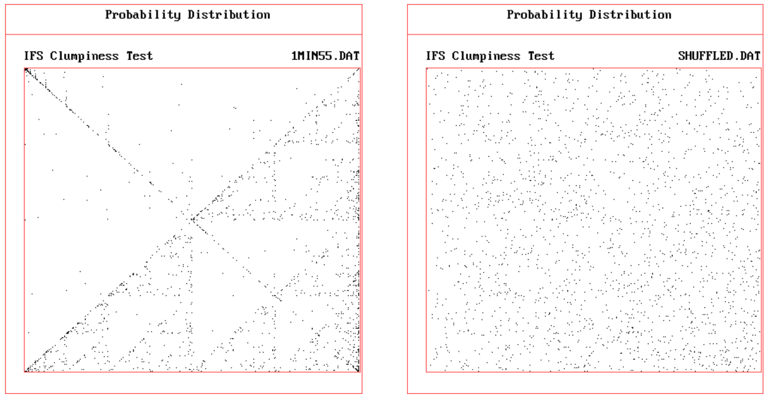
(a) Original data (b) Surrogate data

Figure 10. IFS Clumpliness Maps for One-minute Flow (Station 49)



(a) Original data (b) Surrogate data

Figure 11. IFS Clumpliness Maps for One-minute Flow (Station42)



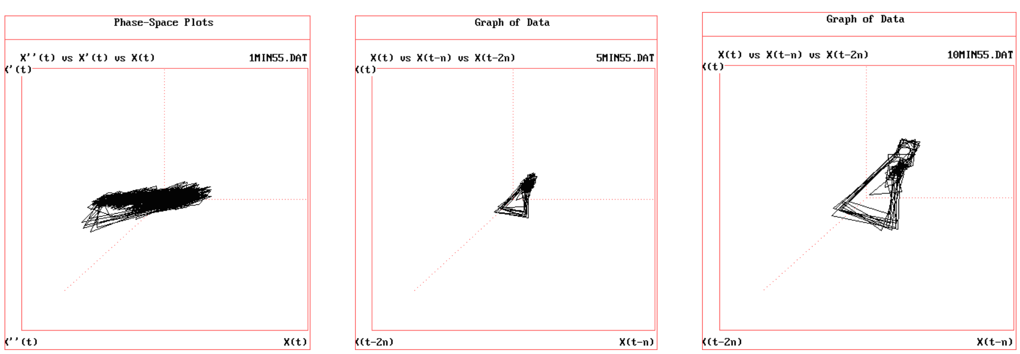
(a) Original data (b) Surrogate data

Figure 12. IFS Clumpliness Maps for One-minute Flow (Station55)

5. MORE EVIDENCE

The aforementioned tests based on Lan's parsimony procedure conclude that one-minute flows exhibit chaotic dynamics, but the chaos will disappear if the same data are measured by five-minute and ten-minute counts. The results also conclude that five- or ten-minute flows are likely quasi-periodic motions.

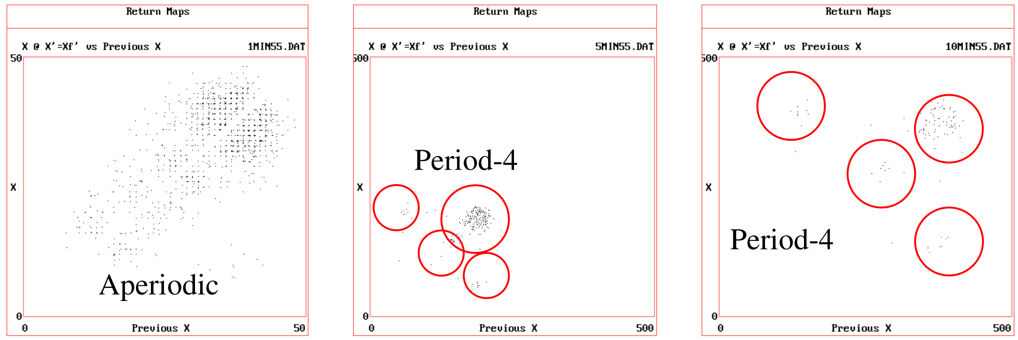
To further verify the above conclusions, we make use of the phase space plots and return maps. Taking station 50 as an example, the phase space plots of different time scales are demonstrated in Figure 13. It is interesting to note that the cycling phenomena become more obviously for the longer-term counts than the shorter-term counts. The cycling structures in Figures 13 (b) and (c) suggest the time series quasi-periodic, not chaotic.



(a) One-minute Flow (b) Five-minute Flow (c) Ten-minute Flow

Figure 13. Phase Space Plots at Station 50

Figure 14 illustrates the return maps of different time scales. These figures provide even stronger evidence for the five-minute and ten-minute flows, which reveal quasi-periodic with period-4. In comparison, the one-minute flows are scattered within the return map, indicating that it is aperiodic.



(a) One-minute (b) Five minute (c) Ten minute

Figure 14. Return Maps at Station 50

6. DISCUSSIONS AND CONCLUSIONS

The roadway traffic flows are derived from travel demands for goods and people, thus the traffic patterns are fully reflected by the trip decisions, including origin/destination, departure time, mode and route choice, made by the road users. If we look at the roadway traffic flow dynamics by examining the hourly flow time series at any location, the trace (one-dimensional trajectory) plot of the flow time series is typically not reproducible from day to day. If we repeat the observation another day under apparently identical conditions, the new hourly flow plot may be nearly, but not exactly, the same as the previous days. The hourly flow plots generally have wiggles in different days and most previous researches have treated such non-reproducible traffic flow dynamics as stochastic. However, if the same traffic time series are counted in a short time interval (e.g., one-minute or even shorter) rather than one hour, we may visualize more conspicuous fluctuations and larger wiggles. It is interesting to notice that the short-term traffic flow patterns never repeat themselves, but the patterns from day to day look very alike, suggesting that there must intrinsically exist some deterministic rules governing the nature of such short-term flow patterns.

The intrinsic rules could be a combination of several effects. Macroscopically, the majority of trip makers might get to work by 9 am and take off at 5 pm in the workdays. They might depart from homes or leave their work places at approximately the same times, using the same modes, and/or choosing the same routes everyday. These regularities could lead to similar flow patterns from day to day. Moreover, the roadway capacity at any location would limit the maximum number of vehicle throughputs in such a way that the observed flow rates are always bounded within two extreme values: zero and maximum (capacity) flows. However, the flow dynamics can never trap at fixed points or stable equilibria at both extreme points. On one hand, as the trip demand is lulled in the midnight, one would still anticipate some background traffic in the road networks; on the other, as the demands far exceed the roadway capacity during rush hours, at most saturated (near capacity) flows would be observed.

Microscopically, individual driver in any circumstance always controls his or her vehicle at a desirable speed with safe spacing that best interacts with the roadway environments and neighboring vehicles. The presence of human behavior makes the traffic systems more complicated than many other physical systems that do not involve human behavior. There are aggressive and less aggressive drivers. Even facing the same situation, some will brake, others will accelerate; some will stay in one lane by following the lead vehicles, others will zigzag constantly between lanes. Due to the heterogeneity across vehicles and drivers, the microscopic traffic properties are always fluctuating over time. In sum, the above-mentioned macroscopic traffic regularities and microscopic traffic irregularities could have generated the aperiodic flows, which exhibit very similar patterns from day to day but never repeat themselves, which might be characterized as a chaotic system.

By employing Lan's parsimony testing procedure, this study has found that the same traffic time series data measured by different time scales have displayed apparently different nonlinear dynamical behaviors. The empirical traffic data drawn from the United States I-35 Freeway morning hours have shown that chaotic phenomena exhibit in the one-minute count; however, if measured in 5-minute and 10-minute, the same traffic time series data would become quasi-periodic motions.

The meanings and practical implications of "chaotic" nature of one-minute traffic and of "quasi-periodic" nature of five- or ten-minute traffic volume patterns are manifold. In traffic prediction, if measured with longer time interval such as five- or ten-minute, one may make use of the quasi-periodic motions of traffic time series by using seasonal ARIMA, wavelet analysis, or Fourier analysis techniques. However, if measured with shorter time interval such as one-minute, the above techniques may fail to perform the prediction well. Nonetheless, one can take advantages of the good features of intrinsic determinism of chaos to construct appropriate prediction models through state-space reconstruction techniques.

The configurations, such as number of lanes, of freeway may differ from station to station in this study, for instance, the detector stations can be closely located to either exit or entrance ramps. We analyze the traffic flows by using the average lane directional volume at each station to avoid the heterogeneity of geometry configurations may cause. A comparison of the nature of traffic patterns caused by different geometric configurations deserves further exploration.

Our conclusions are based on the flows drawn from selected eight stations of the United States I-35 Freeway from 6 am to 9 am for 10 weekdays. Different results would be anticipated with different times of day such as midnight, afternoon peak or off-peak. Moreover, it is interesting to examine if the nonlinear dynamical properties alter if other environmental conditions change, such as different roadways (including surface roads), different counties, etc. These issues also deserve further study.

ACKNOWLEDGEMENTS

This paper is part of the research project granted by National Science Council, ROC under contract NSC-92-2211-E-009-058. The authors are indebted to Dr. C. J. Lan of the University of Miami for providing the traffic time series data.

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