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Modeling traffic flow correlation using DFA and DCCA

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Abstract The focus of the present paper is on the power-law auto-correlations and crosscorrelations in traffic time series. Detrended fluctuation analysis (DFA) and detrended cross-correlation analysis (DCCA) are used to study the traffic flow fluctuations. We find that the original traffic fluctuation time series may exhibit power-law auto-correlations; however, the sign-separated traffic fluctuation signals, both the positive fluctuation signals and the negative fluctuation signals, exhibit anti-correlated behavior. Further, we show that two original traffic speed fluctuation time series derived from adjacent sections exhibit much stronger power-law cross-correlations than the two time series derived from adjacent lanes. Finally, we demonstrate that for two sign-separated traffic fluctuation signals, there exist long-range cross-correlations between the positive fluctuation signals and the negative fluctuation signals, derived from two adjacent lanes, respectively. But, for two same-sign traffic fluctuation signals derived from two adjacent lanes, there is power-law cross-anti-correlation in the variables.

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1 Introduction

The modeling of traffic variable correlations has an important role in the field of conventional traffic behavior modeling and its related applications. Indeed, efforts to develop such models represent an important part of the literature in traffic flow theories [1–12]. Information about auto-correlations and cross-correlations in different traffic variables can tell us much about the magnitude of road traffic stability which, in turn, is vital to assessing the performance of traffic infrastructures.

In the present study, the traffic time series are studied using the detrended fluctuation analysis (DFA) [13–18], a fairly robust and powerful fractal analysis technique, and the detrended cross-correlation analysis (DCCA) [19–21], a generalization of DFA method. The DCCA method especially provides a systematic means to identify and more importantly quantify the cross-correlations between data sets obtained from traffic system. One reason to employ DFA and DCCA methods is to avoid spurious detection of auto-correlations and cross-correlations that are artifacts of non-stationarities in the time series (due to noise superimposed on the collected data and due to underlying trends of unknown origin). Our model uses the traffic data observed on the Lenovo-Bridge highway in the Beijing Third Ring Road (BTRR) as the input data which can be readily collected from conventional point detectors. The preliminary test results suggest the feasibility of estimating correlations in traffic variables using point detector data via the proposed approach.

The paper is organized as follows. In Sect. 2, a brief description of DFA and DCCA is provided. In Sect. 3, the acquisition of traffic data sets is described. In Sect. 4, the results of DFA and DCCA and the calculation of the scaling exponents of auto-correlations and cross-correlations of different traffic variables are provided. The conclusions are summarized in Sect. 5.

2 Proposed methods

2.1 Autocorrelation function analysis

Recently, the study of physical systems displaying long-range power-law correlations has attracted considerable attention. Long-range correlations have been found in a wide number of systems, including biological, physical, economical, geological, and traffic systems [13–18, 22–25].

We consider a record $\{x_k\}$ of $k = 1, \ldots, N$ equidistant measurements. In most applications, the index k will correspond to the time of the measurements. We are interested in the correlation of the values x_k and x_{k+s} for different time lags, i.e. correlations over different time scales s. In order to get rid of a constant offset in the data, the mean $\langle x\rangle = \frac{1}{N}\sum_{k=1}^{N} x_k$ is usually subtracted, $\hat{x}_k = x_k - \langle x\rangle$. Quantitatively, correlations between x-values separated by s steps are defined by the (auto-) correlation function

$$C(s) = \langle \hat{x}_k \hat{x}_{k+s}\rangle = \frac{1}{N-s}\sum_{k=1}^{N-S} \hat{x}_k \hat{x}_{k+s}. \tag{1}$$

If the x_k are uncorrelated, $C(s)$ is zero for $s > 0$. Short-range correlations of the x_k are described by $C(s)$ declining exponentially, $C(s) \sim \exp(-s/s_0)$ with a decay time s_0. For so-called long-range correlations $C(s)$ declines as a power-law

$$C(s) \propto s^{-\gamma} \tag{2}$$

with an exponent $0 < \gamma < 1$. A direct calculation of $C(s)$ is usually not appropriate due to noise superimposed on the collected data x_k and due to underlying trends of unknown origin. Thus, we have to determine the correlation exponent γ indirectly (see Fig. 1). Such trends have to be well distinguished from the intrinsic fluctuations of the system in order to find the correct scaling behavior of the fluctuations. Detrended fluctuation analysis (DFA) [13] is a well-established method

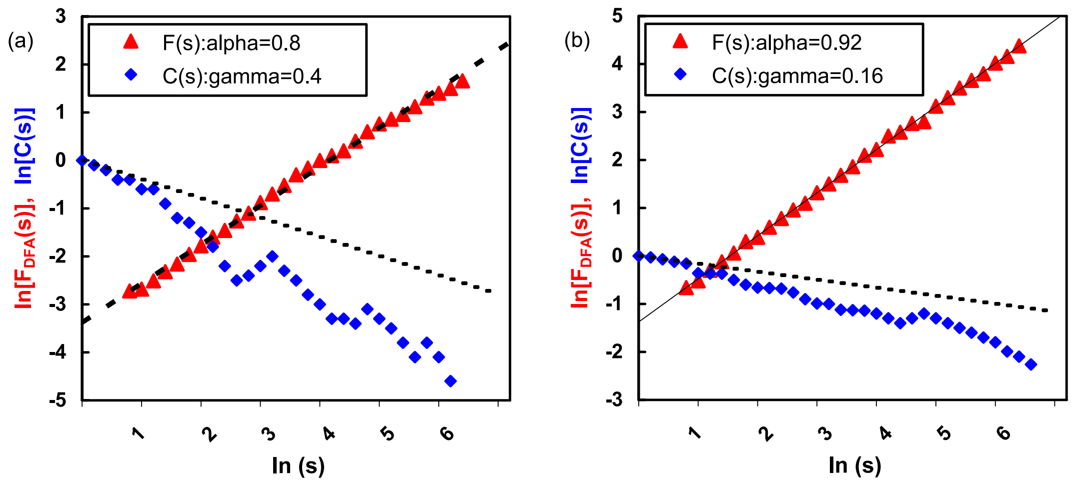


Fig. 1 Comparison of the autocorrelation functions $C(s)$ (decreasing functions) and fluctuation functions $F(s)$ (increasing functions) for the artificial long-range correlated data ($\gamma = 0.4$ and $\alpha = 0.8$, *left*) and the traffic fluctuation data ($\gamma = 0.16$ and $\alpha = 0.92$, *right*). The artificial long-range correlated data have been generated by Fourier filtering [26]; the traffic data are downloaded from the Highway Performance Measurement Project (FPMP) run by Beijing STONG Intelligent Transportation System Co. Ltd, Beijing (see Sect. 3). The *dashed lines* indicate the theoretical curves

for determining the scaling behavior of noisy data in the presence of trends without knowing their origin and shape.

2.2 DFA method

In the last 15 years, Detrended Fluctuation Analysis (DFA), originally introduced by Peng et al. [13], has been established as an important method to reliably detect long-range (auto-)correlations in non-stationary time series. The DFA procedure consists of five steps.
Step 1: Determine the "profile"

$$Y_i \equiv \sum_{k=1}^{i} [x_k - \langle x \rangle], \quad i = 1, \ldots, N \tag{3}$$

of the record $\{x_k\}$ of length N. Subtraction of the mean $\langle x \rangle$ is not compulsory, since it would be eliminated by the later detrending in the third step.
Step 2: Divide the profile Y_i into $N_s \equiv \mathrm{int}(N/s)$ non-overlapping segments of equal length s. Since the length N of the series is often not a multiple of the considered time scale s, a short part at the end of the profile may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end. Thereby, $2N_s$ segments are obtained altogether.
Step 3: Calculate the local trend for each of the $2N_s$ segments by a least-square fit of the series. Then determine the variance

$$F^2(s, v) \equiv \frac{1}{s} \sum_{i=1}^{s} \{Y_{[(v-1)s+i]} - y_{v,i}\}^2 \tag{4}$$

for each segment v, $v = 1, \ldots, N_s$ and

$$F^2(s, v) \equiv \frac{1}{s} \sum_{i=1}^{s} \{Y_{[N-(v-N_s)s+i]} - y_{v,i}\}^2 \tag{5}$$

for each segment $v = N_s + 1, \ldots, 2N_s$. Here, $y_{v,i}$ is the fitting polynomial in segment v. Linear, quadratic, cubic, or higher order polynomials can be used in the fitting procedure (conventionally called DFA1, DFA2, DFA3,...). Since the detrending of the time series is done by the subtraction of the polynomial fits from the profile, different order DFA differ in their capability of eliminating trends in the series. In DFAm (mth order DFA) trends of order m in the profile are eliminated. Thus, a comparison of the results for different orders of DFA allows one to estimate the type of the polynomial trend in the time series.
Step 4: Average over all segments to obtain the fluctuation function

$$F(s) \equiv \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} F^2(s, v) \right\}^{1/2}. \tag{6}$$

It is apparent that $F(s)$ will increase with increasing s. Of course, $F(s)$ depends on the DFA order m. By construction, $F(s)$ is only defined for $s \geq m + 2$.
Step 5: If $F(s)$ increases for increasing s by $F(s) \sim s^\alpha$ with $0.5 < \alpha < 1$, one finds that the scaling exponent α is related to the correlation exponent γ by $\alpha = 1 - \frac{\gamma}{2}$ (see (2)). In this case, we can determine the correlation exponent γ by measuring the fluctuation exponent α (In fact, the scaling exponent α is equivalent with the better known Hurst exponent). We can plot $F(s)$ as a function of s on double logarithmic scales to measure α by a linear fit. A value of $\alpha = 0.5$ thus indicates that there are no (or only short-range) correlations. If $\alpha > 0.5$, the data are long-range correlated. The higher α, the stronger the correlations in the signal are. The case $\alpha < 0.5$ corresponds to long-range anti-correlations, meaning that large values are most likely to be followed by small values and vice versa. Figure 1 shows two examples for the application of the DFA method to long-range correlated data (Fig. 1(a), (b)).

2.3 DCCA method

Cross-correlation is a well-known statistical method used to establish the degree of correlation between two different time series. This is done considering that stationarity characterizes both time series under investigation. Unfortunately, real time series are hardly stationary and to cure that, as a rule, short intervals are considered for analysis. This is not always a valid choice, especially when the time series need to be seen and analyzed as a whole. For this reason, a method that deals with non-stationary time series, named detrended cross-correlation analysis (DCCA) was introduced by Podobnik and Stanley [19]. We shall recall the main points of the algorithm here, in brief.

The DCCA procedure also consists of five steps. The first three steps are essentially identical to the conventional DFA procedure. Consider two time series $\{x_i\}$ and $\{x'_i\}$, where $i = 1, 2, \ldots, N$, and N is the maximum number of samples.

Step 1: Determine the "profile"

$$
\begin{aligned}
Y_i &\equiv \sum_{k=1}^{i}\big[x_k - \langle x\rangle\big], \\
Y'_i &\equiv \sum_{k=1}^{i}\big[x'_k - \langle x'\rangle\big], \quad i = 1, \ldots, N.
\end{aligned} \tag{7}
$$

Step 2: The integrated signals Y_i and Y'_i are divided into boxes of equal length s.

Step 3: In each box of length s, we fit Y_i and Y'_i, using a polynomial function of order l which represents the trend in that box (here linear polynomial is used in the fitting procedure).

Step 4: Calculate the covariance of the residuals in each box:

$$
f^2_{\mathrm{DCCA}}(s, v) \equiv \frac{1}{s}\sum_{k=1}^{s}(Y_k - \tilde{Y}_{k,v})(Y'_k - \tilde{Y}'_{k,v}), \tag{8}
$$

where $\tilde{Y}_{k,v}$ and $\tilde{Y}'_{k,v}$ are the fitting polynomials in segment v, respectively. Then average over all segments to obtain the fluctuation function:

$$
F^2_{\mathrm{DCCA}}(s) \equiv \frac{1}{2N_s}\sum_{v=1}^{2N_s} f^2_{\mathrm{DCCA}}(s, v). \tag{9}
$$

When $\{x_i\} = \{x'_i\}$, the detrended covariance $F^2_{\mathrm{DCCA}}(s)$ reduces to the detrended variance $F^2_{\mathrm{DFA}}(s)$ used in the DFA method.

Step 5: Determine the scaling behavior of the fluctuation functions by analyzing *log–log* plots $F^2_{\mathrm{DCCA}}(s)$ versus s. For two cross-correlated time series $\{x_i\}$ and $\{x'_i\}$, there is a power-law relationship between the fluctuation function $F^2_{\mathrm{DCCA}}(s)$ and the scale s:

$$
F^2_{\mathrm{DCCA}}(s) \sim s^{\lambda}. \tag{10}
$$

The value of λ represents the degree of the cross-correlation between the two time series $\{x_i\}$ and $\{x'_i\}$.

3 Data

Traffic systems have a number of parameters that can be measured. Not all of them, however, can be viewed as interesting or even meaningful for the kind of DFA and DCCA data analysis we conduct. Our time series of experiments in collecting and studying traffic data focused on the speed and volume (the given number of vehicles that pass a given point for a given amount of time; here we record each 2 minutes).

Our study is performed for several time series observed on the Lenovo-Bridge highway in the Beijing Third Ring Road (BTRR). The BTRR is a closed road system without any traffic-signal control. There are three main lanes as well as one or two auxiliary lanes related to on-and-off ramps for each direction. In 2001, 74 remote traffic microwave sensor (RTMS) have been mounted around the ring road to collect real-time traffic data. The periodic time of detecting is 2 min and the distance between two adjacent detectors is about 500 m. Three traffic parameters, volume, speed, and occupancy can be collected by these RTMS detectors in real time.

We use the traffic data recorded each 2 minutes, over a period of about one month, from May 16 to June 17, 2006. The data were downloaded from the Highway Performance Measurement Project (FPMP) run by Beijing STONG Intelligent Transportation System Co. Ltd, Beijing.

To account for auto-correlations and cross-correlations in traffic fluctuation time series, we will analyze eight data sets (each data set has about 21,600 points) as follows (see Fig. 2):

(1) $\{v_i\}$: the average speed of three lanes (Lane 1, Lane 2, and Lane 3) in Section 1;
(2) $\{q_i\}$: the volume of Section 1;
(3) $\{v_i^{(1)}\}$: the speed of Lane 1 in Section 1;
(4) $\{v_i^{(2)}\}$: the speed of Lane 1 in Section 2;
(5) $\{v_i^{(3)}\}$: the speed of Lane 2 in Section 1;
(6) $\{v_i^{(4)}\}$: the speed of Lane 2 in Section 2;
(7) $\{v_i^{(5)}\}$: the speed of Lane 3 in Section 1;
(8) $\{v_i^{(6)}\}$: the speed of Lane 3 in Section 2.

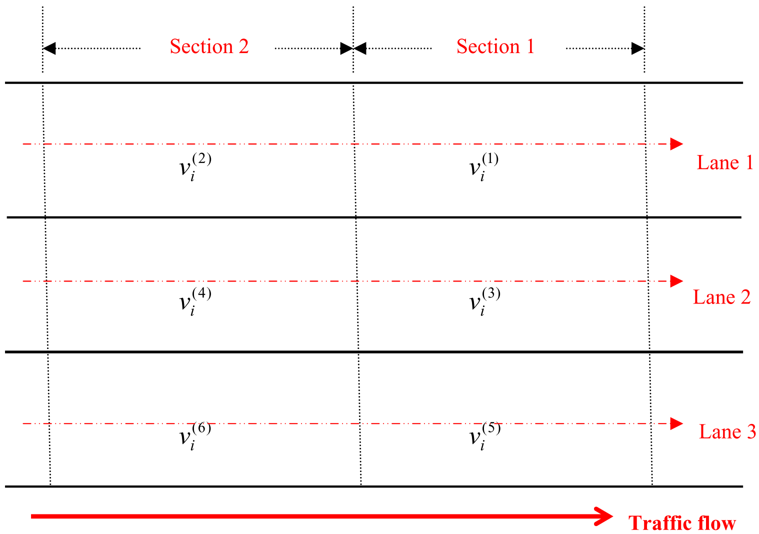
In fact, the traffic variables that we here analyze in the following are $|\hat{v}_i|$, $|\hat{q}_i|$ and $|\hat{v}_i^{(j)}|$, i.e. the time series of absolute values of traffic increment $\hat{v}_i = v_i - v_{i-1}$, $\hat{q}_i = q_i - q_{i-1}$, $\hat{v}_i^{(j)} = v_i^{(j)} - v_{i-1}^{(j)}$ for $j = 1, 2, 3, 4, 5, 6$ and $i = 1, 2, \ldots, N$.

4 Analysis and results

4.1 Autocorrelation and cross-correlation of the original traffic fluctuation series

In order to study the dynamics of the traffic flow over time, we first consider two time series, both of which

Fig. 2 Schematic configuration of the chosen sections of the BTRR



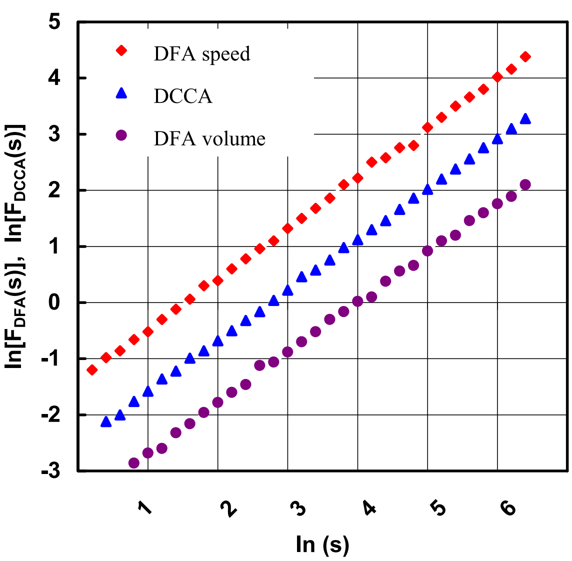


Fig. 3 Power-law autocorrelations and cross-correlations in two time series, $\{|\hat{v}_i|\}$ and $\{|\hat{q}_i|\}$, of absolute values of the successive differences of $\{v_i\}$ and $\{q_i\}$

can be considered as two outputs of traffic system: the traffic speed fluctuation series $\{|\hat{v}_i|\}$ and the traffic volume fluctuation series $\{|\hat{q}_i|\}$. Here, $\hat{v}_i = v_i - v_{i-1}$, $\hat{q}_i = q_i - q_{i-1}$, and $\{v_i\}$ are the average speed of three lanes (Lane 1, 2, and 3) in Sect. 1 and $\{q_i\}$ the volume of Sect. 1 (see Fig. 2).

Figure 3 shows that each of two time series of absolute values of the successive differences of $\{v_i\}$ and $\{q_i\}$ exhibits power-law auto-correlations with similar scaling exponents. Figure 3 also shows that cross-correlation between $\{|\hat{v}_i|\}$ and $\{|\hat{q}_i|\}$ exists and can be fit a power law s^λ with exponent $\lambda = 0.91$, practically, approximately equal to the exponent calculated for each of two time series $\{|\hat{v}_i|\}$ and $\{|\hat{q}_i|\}$. We find that DFA curves of $\{|\hat{v}_i|\}$ and $\{|\hat{q}_i|\}$ and DCCA curve are very similar, and can be approximated with power laws $F_{\text{DFA}}(s) \sim s^\alpha$ with scaling exponents $\alpha_v = 0.92$ and $\alpha_q = 0.90$, and $F_{\text{DCCA}}(s) \sim s^\lambda$ with $\lambda = 0.91$.

It is worth noticing the fact that, according to the definition of cross-correlation [19], each of the two variables at any time depends not only on its own past values but also on past values of the other variable.

Next, we investigate the power-law cross-correlations between two traffic speed fluctuation variables $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(2)}|\}$, which are derived from two adjacent sections of a highway and simultaneously recorded every two minutes (see Fig. 2). The DFA curves in Fig. 4 show that each of two time series of absolute values of the successive differences of speed variables $\{v_i^{(1)}\}$ and $\{v_i^{(2)}\}$ exhibits power-law autocorrelated behavior, indicating that a large increment is more likely to be followed by a large increment. Figure 4 also illuminates that, besides autocorrelations, the traffic time series of two adjacent sections exhibit power-law cross-correlation, indicating that a large increment in one traffic variable is more likely to be followed by large increment in the other traffic variable. Moreover, we find that $F_{\text{DCCA}}(s)$ can be approximated with power laws: $F_{\text{DCCA}}(s) \sim s^\lambda$ with scaling exponents $\lambda = 0.76$.

Further, we consider the case when two time series of variables $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(3)}|\}$ are derived from

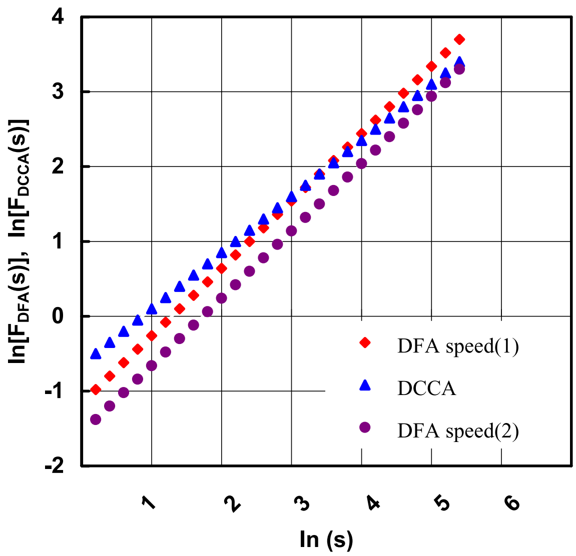


Fig. 4 Power-law autocorrelations and cross-correlations between two traffic speed fluctuation variables $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(2)}|\}$, which are derived from two adjacent sections of a highway and simultaneously recorded every two minutes (see Fig. 2)

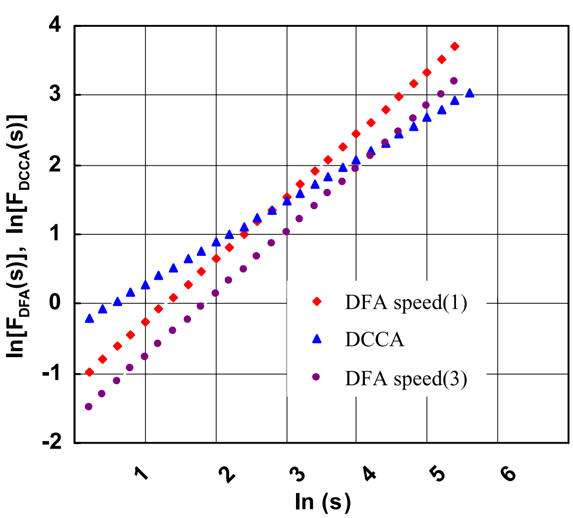


Fig. 5 Power-law autocorrelations and cross-correlations between two traffic speed fluctuation variables $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(3)}|\}$, which are derived from two adjacent lanes (see Fig. 2)

two adjacent lanes (see Fig. 2). From Fig. 5, we can see that the cross-correlation between two time series of absolute values of the successive differences of the speed variables $\{v_i^{(1)}\}$ and $\{v_i^{(3)}\}$ exists and can be fit a power law s^{λ} with exponent $\lambda = 0.61$.

In addition, we also find that power-law cross-correlation exists between the two time series of variables $\{|\hat{v}_i^{(2)}|\}$ and $\{|\hat{v}_i^{(3)}|\}$, which are derived from different lanes (see Fig. 2); however, their cross-correlation is not stronger than the time series of two adjacent sections, concretely $\lambda = 0.53$.

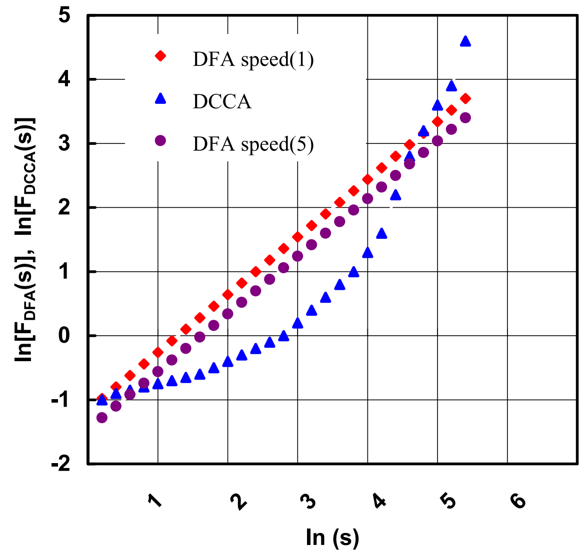


Fig. 6 DCCA analyses of the power-law cross-correlations between two traffic speed fluctuation variables $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(5)}|\}$, which are derived from two non-adjacent lanes

Finally, we investigate the power-law cross-correlation between two traffic variables $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(5)}|\}$, which are derived from two non-adjacent lanes of a highway and simultaneously recorded every 2 minutes (see Fig. 2). In Fig. 6, we find that even though both $\{|\hat{v}_i^{(1)}|\}$ and $\{|\hat{v}_i^{(5)}|\}$ are power-law auto-correlated; these two time series are not power-law cross-correlated with an unique exponent, but either short-range cross-correlated or not at all cross-correlated.

We stress that, regarding other coupled variables $\{|\hat{v}_i^{(3)}|\}$ and $\{|\hat{v}_i^{(5)}|\}$, $\{|\hat{v}_i^{(4)}|\}$ and $\{|\hat{v}_i^{(6)}|\}$, $\{|\hat{v}_i^{(3)}|\}$ and $\{|\hat{v}_i^{(6)}|\}$, etc.; there are the same results for the power-law cross-correlations between them as listed above in the respective cases.

4.2 Autocorrelation and cross-correlation of the positive and negative fluctuations

To further exemplify the potential utility of the DFA, and especially, the DCCA method for analyzing real-world data, we study traffic fluctuation signals with power-law correlations by decomposing the traffic fluctuation series $\hat{v}_i = v_i - v_{i-1}$ into a positive fluctuation signal $\hat{v}_{pi}$ and a negative fluctuation signal $\hat{v}_{ni}$ and analyze their auto-correlation and cross-correlation properties.

Traffic systems exhibit complex dynamics, associated with the presence of many components interacting over a wide range of time or space scales. These often-competing interactions may generate an output signal with fluctuations that appear "noisy" and "erratic" but reveal scale-invariant structure [22–25]. Therefore, we next examine the auto-correlation and cross-correlation characteristics of the positive and negative fluctuation series. These characteristics reflect the underlying interactions in traffic system.

Our study is performed for several sign-separated time series decomposed from the traffic speed fluctuation variables $\{\hat{v}_i^{(1)}\}$ and $\{\hat{v}_i^{(3)}\}$, which are derived from two adjacent lanes (see Fig. 2).

In our method, the original fluctuation signal $\hat{v}_i^{(1)}$ ($i = 1, 2, \ldots, N$) is decomposed into two sign-separated components; a positive fluctuation signal:

$$\hat{v}_{pi}(1) = \begin{cases} \hat{v}_i^{(1)} & \text{if } \hat{v}_i^{(1)} > 0, \\ 0 & \text{otherwise,} \end{cases}$$

and a negative fluctuation signal:

$$\hat{v}_{ni}(1) = \begin{cases} \hat{v}_i^{(1)} & \text{if } \hat{v}_i^{(1)} < 0, \\ 0 & \text{otherwise.} \end{cases}$$

In like manner, $\hat{v}_i^{(3)}$ can be decomposed into $\hat{v}_{pi}(3)$ and $\hat{v}_{ni}(3)$. Then $\hat{v}_i^{(1)} = \hat{v}_{pi}(1) + \hat{v}_{ni}(1)$ and $\hat{v}_i^{(3)} = \hat{v}_{pi}(3) + \hat{v}_{ni}(3)$. In general, by the superposition rule of the detrended fluctuation analysis method in the reconstruction of the signal from the summation of two fluctuation signals $f(t)$ and $g(t)$, there exists a well-known mathematical relation between their root mean square (rms) fluctuation functions F_f, F_g and F_{f+g} [17].

We first analyze auto-correlation and cross-correlation in the positive fluctuation signal $\hat{v}_{pi}(1)$ and $\hat{v}_{pi}(3)$, derived from two adjacent lanes. The DFA curves in Fig. 7 show that each of the two positive time series $\hat{v}_{pi}(1)$ and $\hat{v}_{pi}(3)$ exhibits anti-correlated behavior with DFA exponents $\alpha_p(1) = 0.38$, $\alpha_p(3) = 0.35$, indicating that a large increment is more likely to be followed by a large decrement. Figure 7 also shows that the positive fluctuation time series of the two adjacent lanes exhibit power-law cross-anti-correlations, that is, large values in one series are followed by smaller ones in the other. Moreover, we find

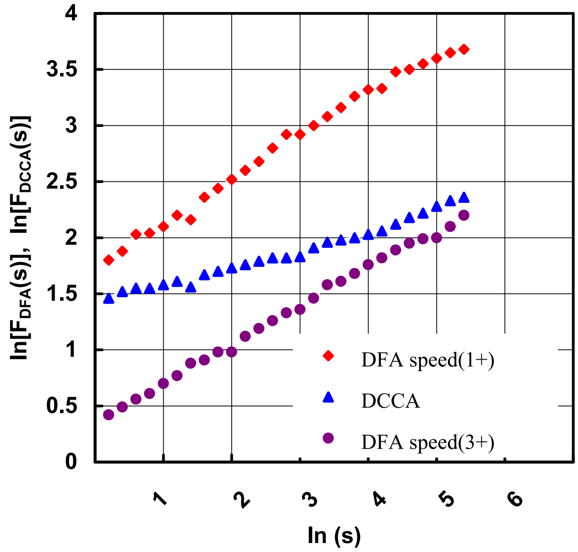


Fig. 7 Autocorrelations and cross-correlations in the positive fluctuation signals $\hat{v}_{pi}(1)$ and $\hat{v}_{pi}(3)$, derived from two adjacent lanes

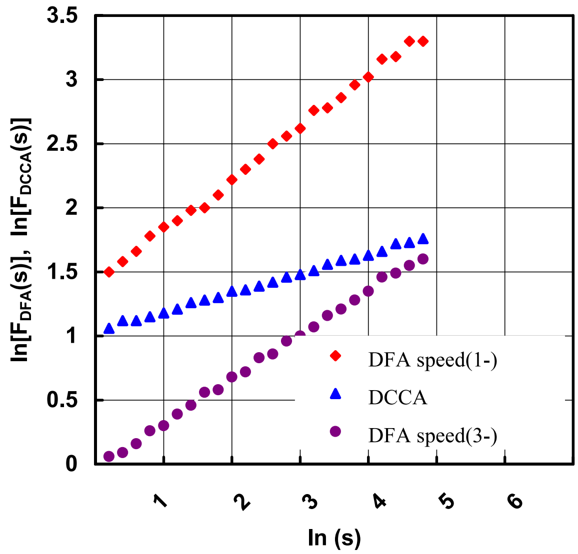


Fig. 8 Autocorrelations and cross-correlations in the negative fluctuation signals $\hat{v}_{ni}(1)$ and $\hat{v}_{ni}(3)$, derived from two adjacent lanes

that $F_{\text{DCCA}}(s)$ can be approximated with power laws: $F_{\text{DCCA}}(s) \sim s^{\lambda}$ with scaling exponents $\lambda = 0.16$.

For the negative time series $\hat{v}_{ni}(1)$ and $\hat{v}_{ni}(3)$, we obtain similar results by analyzing the auto-correlation and cross-correlations shown in Fig. 8. We find that the two negative fluctuation signals also exhibit the

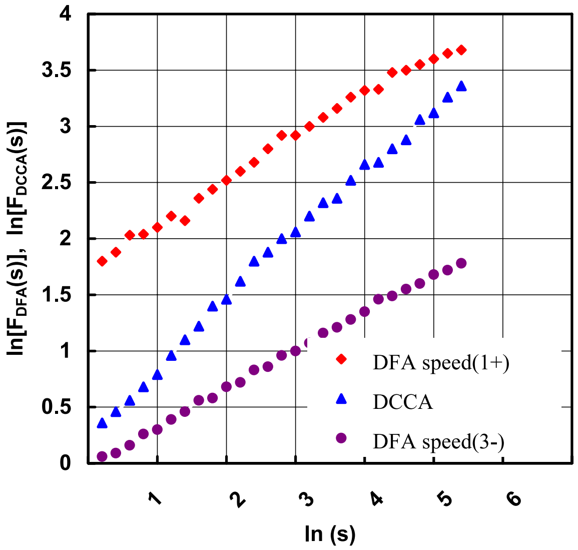


Fig. 9 Autocorrelations and cross-correlations in the positive fluctuation signal $\hat{v}_{pi}(1)$ and the negative fluctuation signal $\hat{v}_{ni}(3)$, derived from two adjacent lanes

anti-correlated behavior with DFA exponents $\alpha_n(1) = 0.40$, $\alpha_n(3) = 0.36$, and DCCA exponent $\lambda = 0.16$.

Finally, the DFA and DCCA of the positive time series $\hat{v}_{pi}(1)$ and the negative time series $\hat{v}_{ni}(3)$ are shown in Fig. 9. It is worth noticing the fact that the fluctuation function $F_{\mathrm{DCCA}}(s)$ indicates power-law cross-correlated behavior with DCCA exponent $\lambda = 0.58$, while both $\hat{v}_{pi}(1)$ and $\hat{v}_{ni}(3)$ exhibit anti-correlations. This is a rather different situation, but nevertheless equally possible. We find that the negative time series $\hat{v}_{ni}(1)$ and the positive time series $\hat{v}_{pi}(3)$ also have similar long-range cross-correlation properties as in Fig. 9.

5 Conclusions

In this paper, we study the power-law auto-correlations and cross-correlations in traffic series by using DFA and DCCA technique. The technique has been implemented on the time series of absolute values of the successive differences of the original traffic variables and the sign-separated time series decomposed from the traffic speed fluctuation variables. Concretely, our main results are as follows:

(1) For the traffic time series of absolute values of the successive differences of $\{v_i\}$ and $\{q_i\}$, we find their power-law autocorrelations;
(2) For the sign-separated traffic time series, $\hat{v}_{pi}(m)$ or $\hat{v}_{ni}(m)$, decomposed from the traffic speed fluctuation variables, both the positive fluctuation signals and the negative fluctuation signals exhibit anti-correlated behavior;
(3) The two absolute values variables, $\{|\hat{v}_i^{(m)}|\}$ and $\{|\hat{v}_i^{(n)}|\}$, derived from adjacent sections in the same lane respectively, exhibit stronger power-law cross-correlations;
(4) The two absolute values variables, $\{|\hat{v}_i^{(m)}|\}$ and $\{|\hat{v}_i^{(n)}|\}$, derived from adjacent lanes in the same section respectively, exhibit weaker power-law cross-correlations;
(5) The two absolute values variables, $\{|\hat{v}_i^{(m)}|\}$ and $\{|\hat{v}_i^{(n)}|\}$, derived from non-adjacent lanes respectively, are not power-law cross-correlated with a unique exponent;
(6) For two same-sign traffic fluctuation signals, $\hat{v}_{pi}(m)$ and $\hat{v}_{pi}(n)$, or $\hat{v}_{ni}(m)$ and $\hat{v}_{ni}(n)$, derived from adjacent lanes in one section respectively, there is power-law cross-anti-correlation in the variables;
(7) For two sign-separated traffic signals, $\hat{v}_{pi}(m)$ and $\hat{v}_{ni}(n)$, decomposed from the traffic speed fluctuation variables, derived from two adjacent lanes in one section respectively, there exist long-range cross-correlation properties between the positive fluctuation signals and the negative fluctuation signals.

We would like to stress that, from the correlation exponent of the traffic data sets we can clarify the relationship between the cross-correlation and the locality where traffic variables are measured. For example, we show that two traffic speed fluctuation parameters derived from adjacent sections exhibit much stronger correlation than the traffic parameters derived from adjacent lanes. Also, if two traffic variables exhibit cross-correlation, each of the two variables at any time depends not only on its own past values but also on past values of the other variable. These results may provide useful information about traffic control mechanisms.

Our present report mainly considers power-law auto-correlations and cross-correlations in the time series of the absolute values of given variables. In fact, we have carefully investigated the long-range cross-correlations between coupled traffic increments $\{\hat{v}_i^{(m)}\}$ and $\{\hat{v}_i^{(n)}\}$ for traffic variables $\{v_i^{(m)}\}$ and $\{v_i^{(n)}\}$, but we do not find long-range cross-correlations between them, although there are power-law auto-correlations themselves.

The findings presented in this paper also suggest the need for further research. The proposed technology, though promising, must be regarded as preliminary because of the limitations of our field data used for model tests. More data in terms of time-varying speed, volume, and density are necessary to adequately evaluate the proposed method. Also, we note that the robust scaling shown in the figures for the traffic time series of given variables must break down for sufficiently long time series. This is because there is a daily periodicity in the traffic, which must appear as a horizontal plateau on the DFA curves. Technologies either extended from or integrated with the proposed method, such as multifractal detrended fluctuation analysis methods of non-stationary time series [15, 23], appear promising to improve the proposed approach. Finally, the findings presented here encourage us to think that this methodology can be extended to cover anomalous but important traffic conditions such as lane-blocking incidents and short-term queue-over flow occurrences. In fact, some effort is already underway in this area.

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