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*Research Article*

# Study on Fractal Multistep Forecast for the Prediction of Driving Behavior

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The application and development of new technology make it possible to acquire real-time data of vehicles. Based on these real-time data, the behavior of vehicles can be analyzed. The prediction of vehicle behavior provides data support for the fine management of traffic. This paper proposes speed and acceleration have fractal features by *R*/*S* analysis of the time series data of speed and acceleration. Based on the characteristic analysis of microscopic parameters, the characteristic indexes of parameters are quantified, the fractal multistep prediction model of microparameters is established, and the BP (back propagation neural networks) model is established to estimate predictable step of fractal prediction model. The fractal multistep prediction model is used to predict speed acceleration in the predictable step. NGSIM trajectory data are used to test the multistep prediction model. The results show that the proposed fractal multistep prediction model can effectively realize the multistep prediction of vehicle speed.

## 1. Introduction

With an increase of traffic flow on highways all over the world, both the risk on traffic safety and the pressure of traffic management increase greatly. The detection and warning of abnormal driving behavior is an indispensable part of intelligent traffic management and monitoring in that it detects abnormal driving behaviors, gives an early warning to possibly affected vehicles, and effectively avoids traffic accidents. With the rapid development of computer technology, image processing technology, and video detecting technology, the accuracy and content of video detection data can provide a solid foundation for abnormal driving behavior monitoring in motor vehicles ([1–4]). Through the application of Hidden Markov random field ([5]), on-board GPS data ([6]), and mobile phone positioned data ([7]), the detection and judgment of abnormal driving behavior becomes reality. Diaz Alvarez et al. present a system for estimating the remaining charge of an electric vehicle by considering the driving behavior measured using a smartphone, using speed and acceleration [8]. Funfgeld et al. introduce a stochastic framework based on an explanatory model and stochastic processes to predict future vehicle dynamics with road network data [9].

Traffic microscopic parameters (instantaneous speed and acceleration) have strong nonlinear characteristics, and fractal theory is a good method to deal with time series data with self-similarity. Firstly, based on the chaos theory, the chaotic characteristics of the microvelocity and acceleration sequence data of the vehicle are analyzed. It is proved that the microparameters of the vehicle are predictable. Then, based on *R*/*S* analysis, it is proved that the two parameters have fractal characteristics, and the prediction model of microscopic parameters is constructed based on the fractal theory. Through the quantification of the index of speed and acceleration time series data, neural network is used to estimate the predictable number of steps, and the prediction model of microparameter-predictable step is obtained. The multistep prediction of vehicle microtraffic parameters is

carried out based on fractal theory. The results show that the prediction model has a good performance.

This shows the model can be used in the prediction of driving behavior. You can develop a warning APP for vehicle abnormal driving behavior. Record the vehicle's real-time positioning data, fractal prediction, predict the driving behavior of the vehicle, identify abnormal driving behaviors such as speed of the vehicle, and provide warning.

## 2. Basic Data Sources

For the purpose of research, the data need to have the following characteristics: (1) freeway vehicle positioning time series data; (2) real-time data of vehicles, with short sampling period, high frequency and high accuracy. According to the predictable analysis of the characteristics of vehicle speed and acceleration, it is not necessary to contain all kinds of driving behavior when studying the prediction method of microscopic parameters. Therefore, in order to reflect the general applicability of the forecasting method and avoid the particularity of the experimental vehicle, this paper chooses American NGSIM trajectory data to support the research. NGSIM stakeholder groups identified the collection of real-world vehicle trajectory data as important to understanding and researching driver behavior at microscopic levels. The NGSIM datasets represent the most detailed and accurate field data collected to date for traffic microsimulation research and development. The US Highway 101 (US 101) dataset was one of several datasets collected under the NGSIM program. The NGSIM trajectory data reflect the information on time series data of the speed or acceleration for the vehicle running on highway. The sampling interval is 0.1s (0.1 second), which can meet the research demand with its large amount of data, and the error of positioning and speed is small enough to be negligible. The specific data attributes are shown in Table 1.

This paper analyzes the speed and acceleration of the vehicle, based on two days' track data which come from the NGSIM trajectory data about I-80 section 05: 00~17: 30 (June 15, 2005) and US-101 section 07: 50~08:35 (April 13, 2005). As shown in Figure 1, the two sections consist of five main lanes, one collector-distributor lane, one entrance ramp, and one exit ramp.

## 3. Fractal Analysis of Microparameters

In this paper, the sampling interval is 0.1 s, 1 s, 2 s, and 4 s. As shown in Figure 2, with the increase of the sampling interval, the chaos of speed and acceleration show a decay trend, so the data of the small interval can be predicted based on the data prediction results of the large sampling interval. The self-similarity of fractal theory can achieve this process well, so the fractal theory can be used to predict the microscopic parameters. Because we have to judge whether the time series data have fractal characteristics, in this paper, we use $R/S$ analysis to calculate Hurst index $H$ [10].

*3.1. Calculation of the Hurst Index to Determine Whether It Has Fractal Characteristics.* For the instantaneous speed or acceleration time series $\{x(t_i) \mid i = 1, 2, \cdots, N\}$, the expectation value of $r$ time series data is

$$(Ex(t))_r = \frac{1}{r}\sum_{i=1}^{r} x(t_i). \tag{1}$$

The standard deviation of the time series data is

$$S(r) = \left\{\frac{1}{r}\sum_{i=1}^{r}\left[x(t_i) - E(x(t_i))\right]^2\right\}^{1/2}. \tag{2}$$

The accumulative dispersion of the series is

$$X(i,r) = \sum_{k=1}^{i}\left[x(t_k) - (Ex(t))_r\right], \quad 1 \le i \le r. \tag{3}$$

The range of the accumulative dispersion of $r$ time series is

$$R(r) = \max_{1\le i\le r} X(i,r) - \min_{1\le i\le r} X(i,r). \tag{4}$$

Hurst index H can be obtained using the following formula:

$$\frac{R(r)}{S(r)} = cr^H, \tag{5}$$

$$\ln\left[\frac{R(r)}{S(r)}\right] = \ln c + H\ln r. \tag{6}$$

Based on the value of $H$, whether or not the time series has fractal characteristics can be judged. When the value is between 0.5 and 1, this indicates that the time series has forward persistence; when the value is between 0 and 0.5, it indicates that it has reverse persistence; the time series is a random data sequence when it is equal to 0.5. Therefore, when $H$ is not equal to 0.5, the time series has fractal characteristics and makes fractal predictions.

*3.2. Calculation of the Fractal Dimension of Microscopic Parameters.* The fractal distribution curve is roughly similar to the exponential distribution, and the value of fractal dimension $D$ is the value of the power exponent, which reflects the fractal strength of the data. The value of fractal dimension $D$ can be obtained using the formula: $D = 2 - H$.

## 4. Prediction of Microparameters Based on Fractal Theory

*4.1. Microscopic Traffic Parameter Prediction Model Based on Fractal Theory.* Based on the above method, the speed and acceleration time series data are shown to have fractal characteristics. Microscopic parameters can be predicted by fractal theory. The prediction steps are as follows:

(1) Select the nearest $r$ time series data from the original speed and acceleration time series data points $\{x(t_i) \mid i = 1, 2, \ldots, N\}$ and then predict the subsequent parameter. Calculate the $H$ value of the sequence based on the nearest $r$ data.

(2) Get the fractal dimension by $D = 2 - H$.

Table 1: NGSIM data attribute.

| Data name | Data description | Unit |
|---|---|---|
| Vehicle ID | License plate number | — |
| Frame ID | Time | 0.1 s |
| $X$ position | The distance between the center of the front and the left edge of the direction of the road | feet |
| $Y$ position | The distance between the center of the front and the right edge of the direction of the road | feet |
| The length and width of the vehicle | The length and width of the vehicle | feet |
| Speed | Vehicle instantaneous speed | feet/s |
| Acceleration | Vehicle acceleration | feet/s$^2$ |
| Type of vehicle | (1) motorbike; (2) car; (3) truck | — |
| Lane recognition | Lane number | — |
| The former car | The number of the former car | — |
| The latter car | The number of the latter car | — |
| Spacing | Space headway | feet |
| Headway | Time headway | s |

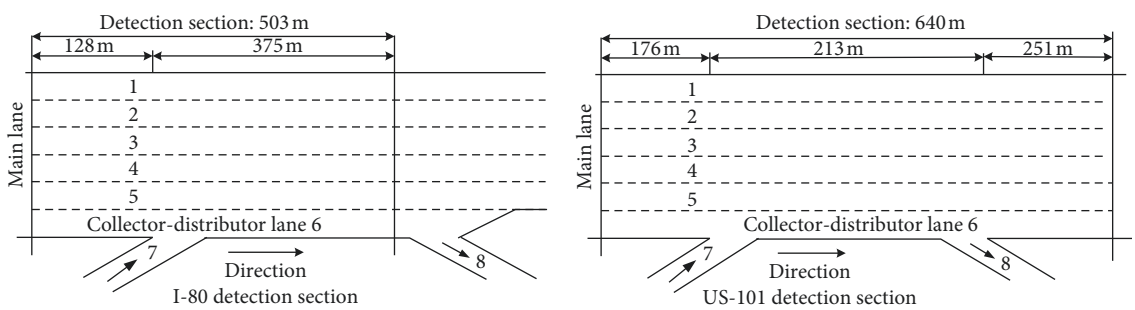


Figure 1: (a) I-80 and (b) US-101 detection section schematic sections.

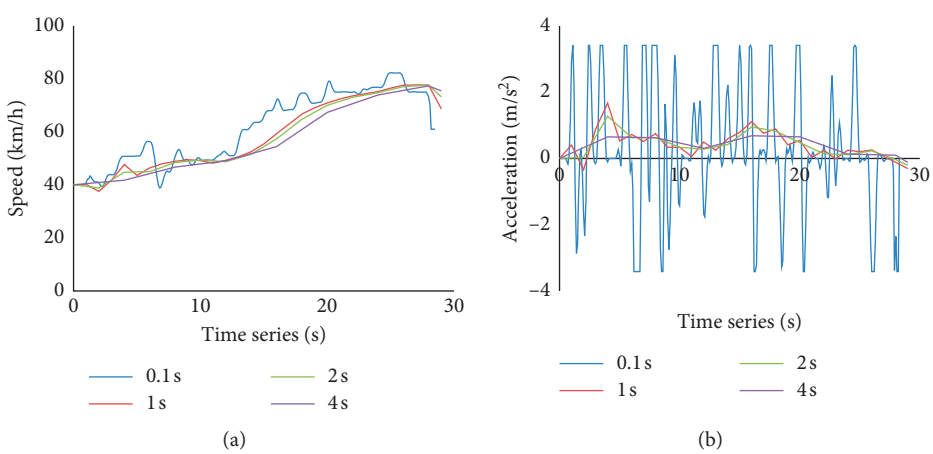


Figure 2: Microcosmic parameter time series curve.

(3) Accumulate the given time series:

$$S(1, j) = x(t_j), \tag{7}$$

$$S(2, j) = S(1, 1) + S(1, 2) + \cdots + S(1, j), \tag{8}$$

$$S(3, j) = S(2, 1) + S(2, 2) + \cdots + S(2, j), \quad j = 1, 2, \ldots, r. \tag{9}$$

Calculate the logarithmic scatter plot of $S(i, j)$ and $j$, and obtain the formula: $\ln(S(i, j)) = \ln c + D' \ln j$. Use linear

regression to estimate the associated dimension $D'$ and $\ln c$. Compare the correlation dimension $D'$ with the fractal dimension $D$ and select the closest combination as the prediction sequence. The prediction is then made by the formula: $\ln(S(i, j)) = \ln c + D' \ln j$. Thereafter, decrease the predicted value $S(i, j)$ step by step to get the forecast value to which the small interval corresponds.

*4.2. Evaluation Indexes of the Predictive Model.* In this paper, the four indexes which are average absolute percentage error MAPE and RMSE are used to analyze the prediction effect of the fractal prediction model on vehicle speed and acceleration sequence. The calculation formulas of each index are as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|F_i - R_i|}{R_i} \times 100\%, \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(F_i - R_i)^2}, \tag{11}$$

where $F_i$ represents predictive value, $R_i$ represents actual value, and $n$ represents the number of samples.

## 5. Multistep Prediction Model of Microscope Parameters

*5.1. Quantification of the Microparameter Characteristic Index.* Affected by some factors, such as roads, traffic composition, traffic condition, and driver's behavior, the microscopic parameter of vehicles will show different dynamic characteristics at different times. Even if with the same prediction method and accuracy requirement, the predictable multisteps will still vary at different times. Therefore, the prediction error will increase if we use a fixed-step prediction model. We can, instead, find the value within a predictable multistep model and decrease the prediction error caused by fixed-step prediction; we can also enhance the prediction accuracy if we analyze the status characteristics of parameters and determine the dynamic predictable steps in advance.

The estimation of step number for microparameter prediction must find the maximum predictable steps when the prediction accuracy can reach a certain requirement. This reduces the prediction time and enhances the accuracy if we can determine the predictable steps of speed and acceleration in a certain state. Some researchers suggest that the predictable steps are approximately equal to the maximum value of the inverse of exponential of Lyapunov when predicting the time series data based on chaos theory. However, if we find the prediction parameters based on fractal theory, the predictable steps might be different, and it is hard to reflect the influence of time series data characteristics of speed and acceleration. Therefore, this paper analyzes the time series characteristic of speed and acceleration and extracts the corresponding indicators and quantifies the indexes. By analyzing the correlation of those indexes and predictable steps, we establish the estimation model.

Microscopic traffic parameter data have obvious dynamic, periodic, trending, nonlinear, and uncertain characteristics, and these characteristics have a certain relationship with their predictable steps. Time series analysis is a statistical method of dynamic data processing. It can not only reveal the evolutionary law of a phenomenon itself but also describe the inherent quantitative relationship between a phenomenon and other phenomena from a dynamic perspective law. Therefore, this paper selects the average development level, average growth, average development speed, volatility, trend, uncertainty, and other indicators to describe the characteristics of short-term microscopic traffic parameter data series. In order to avoid redundancy, six parameters including average development level, average growth, average development speed, volatility, trend, and uncertainty are finally determined through correlation analysis.

Average level of development reflects the general development level of speed and acceleration in the period of time. The formula is as follows:

$$\overline{a} = \frac{(a_1/2) + a_2 + a_3 + \cdots + (a_n/2)}{n-1}. \tag{12}$$

Average growth reflects the average growth of each positioning over a period of time. The formula is as follows:

$$\overline{m} = \sum_{i=2}^{n}\frac{y_i - y_{i-1}}{n-1}. \tag{13}$$

Average development speed reflects the average degree of change in the period of time. The formula is as follows:

$$\overline{v} = \sqrt[n]{\frac{y_n}{y_0}}. \tag{14}$$

The above time series characteristics can reflect the change trend of whole time series to a certain extent, but the dynamic fluctuation and uncertainty of microscopic parameters are not reflected. Therefore, this paper proposes the volatility index, trend index, and uncertainty index of time series data of speed and acceleration.

For volatility characteristics of speed and acceleration sequence data, we use variance and coefficient of variation to reflect the degree of data discretization, where the variance reflects the absolute volatility, while the coefficient of variation is reflected in the relative volatility, as follows:

$$B(t) = \frac{\sqrt{\sum_{i=1}^{n}\left(\left(x(t_i)^2 - \overline{x(t)}^2\right)/(n-1)\right)}}{\overline{x(t)}}. \tag{15}$$

In the formula, $B(t)$ represents volatility index; $n$ represents the total length of the time series data; $x(t_i)$ represents the data when time window is equal to $t_i$; and $\overline{x(t)}$ represents the mean of all the data in the time window.

The movement of the vehicle has a change process, so the microscopic parameters of the vehicle also show different trend characteristics, such as rising trend, decreasing trend, and stable trend. For the different trends, the number of

predictable steps may be different. In this paper, the trend characteristics of the microscopic parameters are quantified, and the relationship between the predictable steps and microscopic parameters is analyzed:

$$Q(t) = \sum_{i=1}^{n-k} \frac{(x(t_{i+k}) - x(t_i))/k}{n-k}. \tag{16}$$

In the formula, $Q(t)$ represents trend index and $k$ represents the gradient of the data sequence in slope calculation.

Uncertainty index refers to the randomness of the data; generally, we use information entropy to reflect the uncertainty of the data sequence. This paper uses fuzzy entropy index to reflect the uncertainty of microscopic parameters. If the calculated length has $n$ uncertainty indexes of the time data sequence, the ambiguity of each microparameter value is calculated first. The formula is as follows:

$$p_i = \frac{x(t_i)}{\sum_i^n x(t_i)}. \tag{17}$$

Then, the calculated uncertainty indexes based on the ambiguity of each value are as follows:

$$H = \log_2 n + \sum_{i=1}^{n} p_i \log_2 p_i. \tag{18}$$

In the formula, $n$ represents the last $n$ time series samples and $p_i$ represents the ambiguity of the $n$ data value.

*5.2. Analysis of Characteristic Indexes.* It is possible to predict the data sequence based on the fractal prediction theory; however, due to the timeliness of the actual data, the prediction steps are related to the basic data, and the predictable steps of other data sequences are different. This paper quantifies the volatility, trend and uncertainty, and other indexes of the basic data series. American expressway data are used as an example to calculate the index. The results are shown in Figure 3.

It can be seen from Figure 3 that the curves of the other five indicators are different from the average level of development. The average level of development reflects the developmental trend of the value during a certain period of time. The figure tells us that vehicles have been in the accelerated trend in this period of time.

This paper uses the fractal prediction model to predict the sample speed data in Figure 3 and calculates the maximum number of predictable steps at each time interval. The error is less than 10%, and finally we get the actual predictable steps of speed at all times. The number of steps is shown in Figure 4. In conjunction with Figures 3 and 4, it can be seen that the other five parameters are inversely proportional to the number of predictable steps in addition to the average level of development. The increase of the volatility index, the uncertainty index, trend index (slope), and speed would result in the decrease of predictable steps.

Similarly, by analyzing the acceleration of the data, the relationship between the acceleration variation characteristic and the acceleration predictable step number can be acquired. The actual predictable step number of the sample data-acceleration is shown in Figure 5. The conclusion is similar to the speed analysis, but the predictable step number of the acceleration is relatively smaller. Therefore, in order to improve the prediction accuracy and predict the efficiency, the acceleration prediction value can be calculated according to the speed prediction value in practical application.

*5.3. Predictable Step Estimation Model of Microscopic Parameters.* After determining the microparameter time series characteristics, this paper studies how to use these indexes to predict microparameters and make dynamic estimations. This is a one-to-many prediction problem to predict the predictable number of steps (an index) of the speed and acceleration based on the chosen six quantified indicators. In addition, the volatility, uncertainty, and trend of time series data are inversely proportional to the predictable steps of the data.

Because the artificial neural network algorithm can deal with many-to-one and nonlinear problems, we use the BP (back propagation) neural network model to predict the dynamic predictable steps of the microscopic parameters. Based on the time series value of speed and acceleration, this paper calculates the average development level, average growth rate, average growth rate, trend index, volatility index, and uncertainty index of the sequence and then standardizes these indexes and uses them as input parameters of the neural network model. The predicted number of steps are used as the output parameter. After, training and tests are conducted for the predictable step estimation model of speed and acceleration. Finally, the predictable step number estimation model of speed and acceleration is obtained.

The study shows that a three-layer BP neural network can deal with any nonlinear continuous function (see [11]). In this paper, we use six parameters which are average level of development, average development speed, average growth rate, trend index, volatility index, and uncertainty index as the input variables, and for the output variable, we use the actual predictable steps. Then, we construct a three-layer neural network and use the sigmoid function as the hidden layer function to select the optimal hidden layer number with the lowest error.

The evaluation index of the predictable step estimation model is similar to that of the microparameter prediction model, which uses the average absolute percentage error MAPE, and the formula is shown in equation (10).

The process of the predictable step number of the microscopic parameter is roughly divided into three steps. These include the online estimation of predictable steps of the microscopic parameters and are shown as follows:

(1) The training of BP neural network: because there are some differences in the overall driving characteristics of vehicles in different regions and different sections, we first target the specific region and depend on the historical vehicle microparameter operation data analysis and then extract the characteristics of indexes and train offline BP neural network estimation

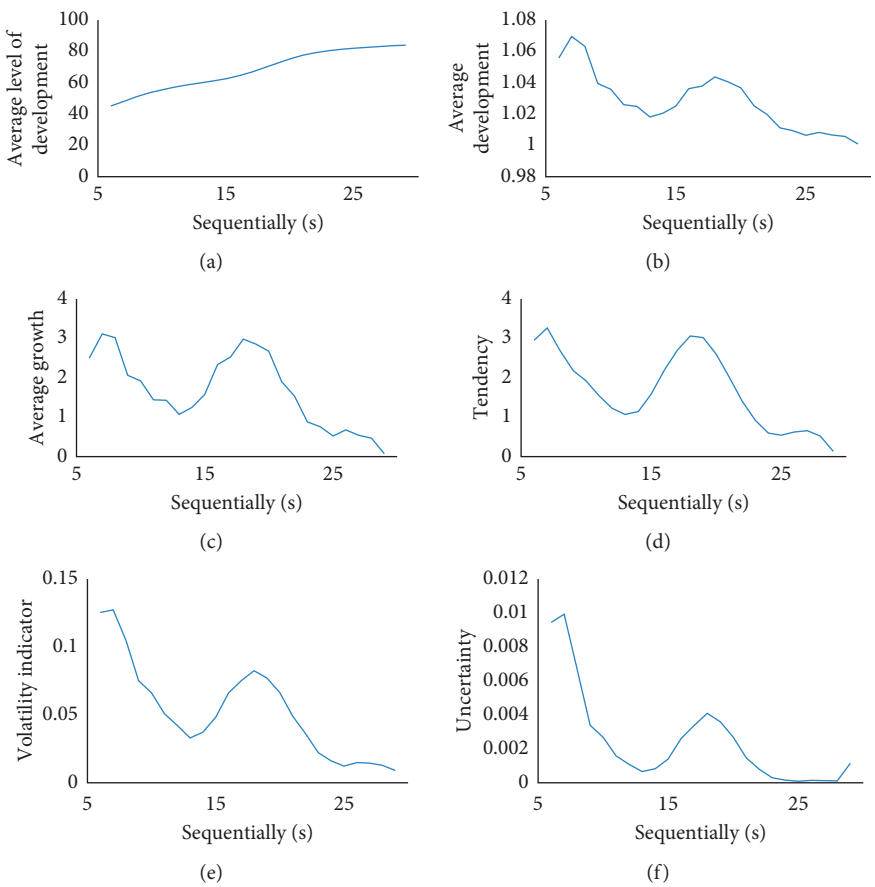


Figure 3: The analysis indexes of speed characteristic: (a) the average level of development of time sequentially, (b) the average development of time sequentially, (c) the average growth of time sequentially, (d) the tendency of time sequentially, (e) the volatility index of time sequentially, and (f) the uncertainty of time sequentially.

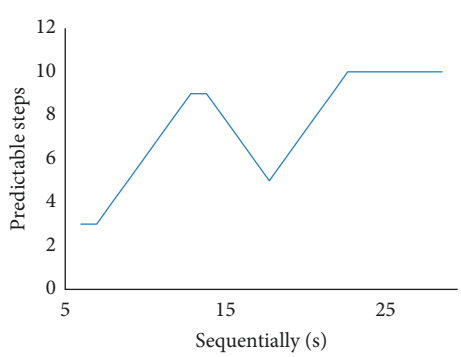


Figure 4: The actual steps for speed.

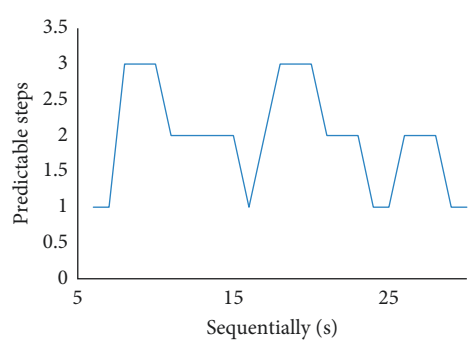


Figure 5: The actual steps for acceleration.

model. In the training of BP neural network, the output variable comes from microscopic traffic parameter prediction model based on fractal theory. Determine predictable steps by judging whether the prediction accuracy (MAPE and RMSE) of the microscopic traffic parameter prediction model based on fractal theory meets the requirements.

(2) The extraction of characteristic indexes: this paper extracts the dynamic characteristic index of the microscopic parameter based on time $t$ and its previous time $k$ series data.

(3) Based on the predictable step number estimation model and the fractal prediction model, the fractal multistep prediction model of microscopic parameters can be carried out. The number of steps in which the sequence parameters of the current time can be effectively predicted is obtained by the predictable step number estimation model, and then the

data within the number of steps are predicted in an iterative manner by the fractal prediction model.

## 6. Analysis of the Model and Case Verification

*6.1. Fractal Analysis of Microparameters.* According to equation (6), this paper, respectively, analyzes the characteristic of speed and acceleration and finally gets the analysis result of speed and acceleration of $R/S$. The result is shown in Figure 6.

According to the analysis results of $R/S$, the $H$ value of the fitted speed time series is 0.99, and the $H$ value of the fitted acceleration time series is 0.74. Thus, the data satisfy the range of $0.5 < H \leq 1$, indicating that it has fractal characteristics, and the time series is persistent and can be predicted accordingly. At the same time, we can see that the speed of $H$ is closer to 1, indicating that the prediction accuracy of speed will be higher.

*6.2. Fractal Prediction Model Analysis of Microparameters.* The fractal prediction model of microscopic parameters is used to predict the sample data. We need to locate the nearest $r$ times, compute the fractal dimension $D$ of the data, sum up the sequence, obtain $S(1, j)$, $S(2, j)$ and other data columns, ask for the dimensionality $D'$ of these data columns, and select the sequence $D'$ corresponding to $S(i, j)$, which is closest to $D$. This paper finds the cumulative sequence of the predicted values after prediction and reduces the cumulative sequence to obtain the predicted data sequence. Therefore, the nearest time length $r$ must be determined before parameter prediction. In the selection of $r$, the accuracy of data prediction and the calculation load should be considered. The value $r$ of this example is determined as 6 in this paper. In this paper, time series position data with steps of 2 to 10 are used for experimental comparison. The prediction accuracy and the number of predictable steps are comprehensively compared, and it is found that it is better to choose $r = 6$. Therefore, this paper selects position data with a time length $r$ value of 6. According to the nearest 6 location data, the prediction of the positioning data at the next time is realized. Based on fractal theory, this paper forecasts the sample data of American expressway, and the fractal dimension of the last 6 location data are calculated, the result of which is shown in Figure 7, and the 4 cumulative sequence curves of speed is shown in Figure 8.

As shown in Figure 7, the $D$ value of speed data is 1.06, and Figure 8 shows that the dimension $D'$ of $S(2, j)$ is 1.0689, which is closest to that of $D$, so we use the $\ln S(2, j) = 1.0689 \ln j + 3.6518$ function to predict $S(2, j + 1)$. Then, the speed prediction data of the next positioning time are calculated by the formula $S(1, j + 1) = S(2, j + 1) - S(2, j)$. The same step is used to obtain the prediction data of other positioning times. The speed and acceleration prediction results of the three samples are shown in Figure 9.

It can be seen from Figure 9 that the speed prediction accuracy is high, but when the speed is abrupt, the speed prediction accuracy is weak, and the prediction results have a certain lag. The predictive evaluation index of the data sample is shown in Table 2.

From Table 2, it can be seen that the acceleration data are relatively large; this is mainly due to the acceleration value itself, which is relatively small and the denominator of the error index value is small. Therefore, some subtle fluctuations can easily lead to large errors. It can be seen from the table that when the speed prediction accuracy of the sample data is high, the average error is low. Compared with the acceleration, it is obvious that the speed is more convenient to predict. In the simulation experiment, there is a large error in the speed prediction. The main reason for this error is that the emergency braking behavior of the vehicle cannot be better predicted. In general, the fractal theory can be used to predict the microscopic data of vehicles well, and the speed prediction is more accurate than the acceleration prediction. Therefore, when predicting the value of acceleration, the acceleration prediction value can be calculated according to the predicted speed value. The average acceleration value of the vehicles between the two locating moments can be calculated by the speed prediction value of two successive positions. This value can then be used as a prediction of acceleration, so the prediction error of acceleration can be reduced, and the prediction performance can be improved.

*6.3. Analysis of Predictable Step Estimation Model for Microparameters.* This paper predicts the data of NGSIM trajectory based on the fractal theory and determines the practicable step length in each time series, as well as the actual prediction step number. We then obtain 280 sets of basic speed time series values and their corresponding actual predictable step numbers. The 280 sets of data are used to calculate the speed characteristics of the 280 indicators, including volatility, trend, uncertainty, and six other indicators. We standardize the data set by maximum and minimum values, and 210 sets of data are trained in the predictable step estimation model to obtain the network model of $6 \times 7 \times 1$ (6 input indicators in the input layer, 7 hidden neurons in the hidden layer, and 1 output parameter). The model can estimate the predictable steps of the time series data and obtain the predictable steps number. The remaining 70 sets of data are tested on the model. The results are shown in Figure 10.

From Figure 10, we can see that the trained neural network has better predictable steps for time series data. The absolute error is less than 15%, and the average absolute percentage error is 9%. It also can be seen from the above figure that when the number of predictable steps of the dataset is small, the accuracy of the predictable step estimation model is relatively higher, but the prediction accuracy is decreased when the number of predictable steps increases.

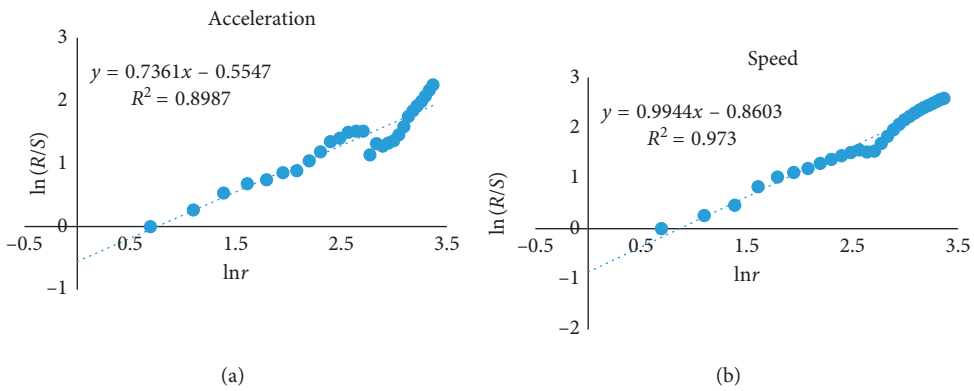


Figure 6: The analysis result of $R/S$ data of NGSIM trajectory data: (a) result of acceleration of $R/S$ and (b) result of speed of $R/S$.

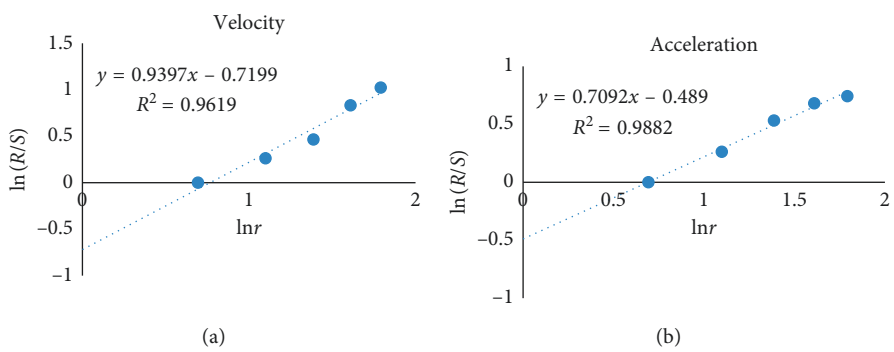


Figure 7: The last 6 data analyses results of $R/S$ graph: (a) acceleration of $R/S$ and (b) speed of $R/S$.

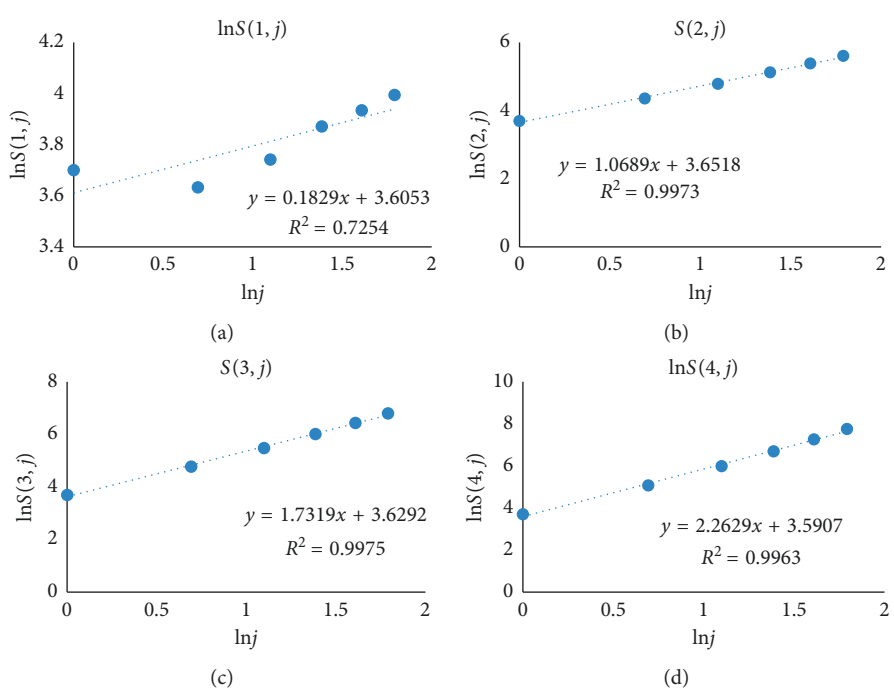


Figure 8: 4 cumulative sequence curves of speed: (a) first, (b) second, (c) third, and (d) fourth.

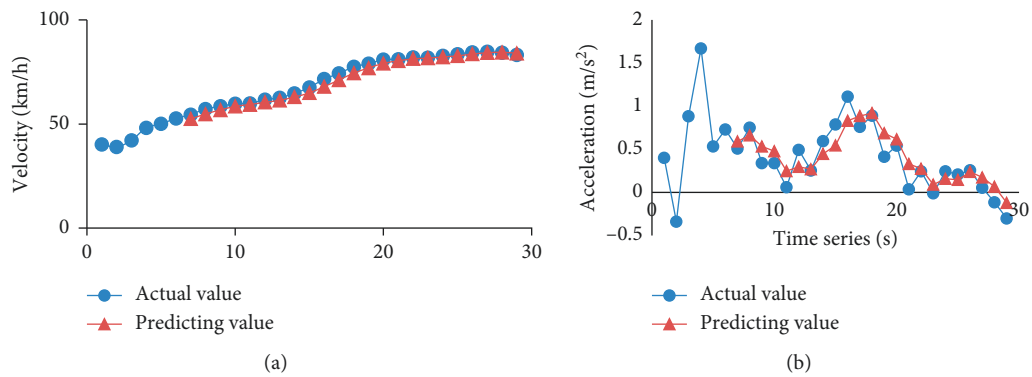


Figure 9: NGSIM trajectory sample prediction results of (a) speed and (b) acceleration.

Table 2: Index table of data prediction and evaluation.

| Data | Parameter | MAPE (%) | RMSE |
|---|---|---|---|
| Example of NGSIM trajectory | Speed | 1.83 | 2.42 |
| | Acceleration | 18.46 | 0.14 |

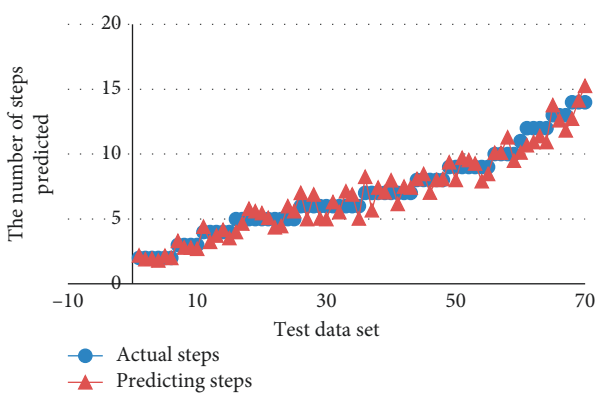


Figure 10: The test results of predictable step model.

## 7. Conclusion

In this paper, the fractal characteristics of microscopic parameters are analyzed, and the fractal prediction model of microscopic parameters is proposed based on feature analysis. In order to improve the prediction speed, this paper analyzes the time series data characteristics of microscopic parameters, including quantitative volatility, trend, uncertainty, and other indicators; then, the fractal multistep prediction model of microscopic parameters is obtained. Finally, according to the time series characteristics of speed and acceleration, we extract the corresponding indicators, quantify all kinds of indicators, analyze the correlation between the indicators and the number of predictable steps, and establish the predictable step estimation model of microscopic parameters. US highway data are used to verify the model, and the results show that the proposed fractal multistep prediction model can effectively realize the multistep prediction of vehicle speed. The model is based on the dynamic calculation of predictable steps, which can achieve as long a prediction as possible, while avoiding large errors caused by fixed-step prediction.

A related paper "Analysis and recognition of highway lane-changing behavior characteristics based on GPS location data" has been published in March [12]. This published paper acquires the lane-changing parameters by exploiting on-board GPS data. Then, the parameters' statistical distribution characteristics of vehicles that change lanes and their surrounding vehicles are analyzed, and the characterization parameters of lane-changing behaviors are simultaneously extracted. On these grounds, the lane-changing identification model is established, haled on the hidden Markov model (HMM). The purpose of the published article and this paper both aim to realize the identification and monitoring of the microscopic state of highway traffic flow. However, the prediction methods used are different. The prediction model of the published paper is based on the hidden Markov model (HMM), while the model in this paper is based on fractal multistep prediction model.

## Data Availability

The data were obtained from American NGSIM trajectory data. The NGSIM datasets represent the most detailed and accurate field data collected to date for traffic microsimulation research and development.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Authors' Contributions

Longhai Yang made the foundation of this paper. Hong Xu designed the experiment. Xiqiao Zhang and Shuai Li carried out experiments. Hong Xu and Wenchao Ji analyzed experimental results and wrote the manuscript.

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