An improved method of short-term traffic prediction

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Abstract

Traffic congestion is one of the most severely disturbing problems of everyday life in Metropolitan areas. An urban traffic network is at its most vulnerable during peak hours and slight fluctuations of capacity may cause severe congestion. An effective way to avoid this phenomenon is to predict and forestall congestion. Therefore the development of an accurate short-term traffic prediction method could have very real and substantial practical benefits by means of linking it with the urban traffic network control system. In this paper, an improved method is proposed which combines the ANN (Artificial Neural Network) model (used for matching the linear trends) with the fractal self-similar model (used for matching the non-linear trends), and sets proper coefficients of the two results with the real data and real-time. Result shows that the improved method can provide a more accurate prediction for short-term traffic flow in an urban area.

Keywords: short-term traffic prediction, prognosis horizon, chaos, ANN (Artificial Neural Network), fractal self-similar model.

1 Introduction

In recent decades growing traffic problems (congestion, emission and noise pollution etc.) have become an increasing disturbing factor both to social and economic life. Therefore, there is a research in ITS for new traffic management and information systems to solve these problems. One essential component of such systems is the prediction of traffic states (such as volume, speed and density). The information of future demand can be provided to traffic control
centres to prevent a jam in advance by using traffic lights or variable message signs, or passing information to the drivers by means of radio broadcasts or dynamic route guidance systems. The principle of this means is to utilize the urban road network maximally, however, the cost of unblocked travel route is the increase of whole travel time in the road network i.e. to allocate the traffic volume to the network evenly [1,2].

So short-term traffic prediction which prognosis horizon ranges from 1min to 15min(2-5min use for road control, 5-15min use for traffic inducement) is vital to ITS system. However, literatures [3] showed that the problem of short-term forecasting is not straightforward: the traffic data that collected from road site loops are also noisy; many validated and random factors influence the changes of short-term traffic volumes, i.e. the short-term traffic is the output of multi-dimensional complex system.

Previous literatures about traffic volume prediction method always fall in two categories: one is based on the dynamic information of the upstream traffic flow (such as Kalman filter model [5,6], ANN model [2]), the other is based on the time series historical data itself for the traffic time series already provide predictive data for all days of a sample class (such as constant model [1], ANN model [3], Arima model [7], time delay recurrent model [2] and fractal self-similar model [9,10,11]).

Based on previous researches, this paper tries to find a method that can quantify the error changes of different models by means of analysing prediction errors, and combining different model therefore minimizes prediction errors. The remainder of the paper is structured as follows. In the next section the principle of prediction is discussed. In section 3, ANN (back-propagation neural network) model and fractal self-similar model are used to match the real data. In the following, an improved method is proposed to minimize the prediction error by means of analysing dynamic errors of perspective model and using proper parameters to combine the two models. The paper closes with a summary and an outlook.

2 The principle of short-term traffic volume forecasting

2.1 Traffic prototype analysis

The central element in quantum physics is that it refers exclusively to chance, that is to say never to certainty. This suggests that we cannot predict a single specific consequence, but only a number of possible results all within a given range of predetermined levels of probability [4]. This implies, we can’t predict the traffic flow volume exactly, i.e. the error of prediction companies with the forecasting process enduringly. This can explain why the more difficulty and errors when we lessen the prognosis horizon, because of the increasing uncertainty when we shorten statistic interval of the traffic flow. Consider two adjacent junctions in a street network as shown in Fig.1. The factors that influence traffic flow are enumerated and discussed.
In Fig.1, $q_0$ is the single direction traffic flow in site A, it influenced by the upper streams such as $q_{1S}$, $q_{2R}$, $q_{3L}$, $q_4$ and $q_5$, where:

- $q_0$: the traffic flow volume at downstream location A
- $q_{1S}$: the straight vector of $q_1$,
- $q_{2R}$: the right-turn vector of $q_2$,
- $q_{3L}$: the left-turn vector of $q_3$,
- $q_0'$: the sum of $q_{1S}$, $q_{2R}$ and $q_{3L}$ in the upstream section road
- $q_4$: the loss volume of $q_0'$,
- $q_5$: the increase volume of $q_0'$.

If the volume and speed (means the travel time of every vehicle) of $q_{1S}$, $q_{2R}$, $q_{3L}$, $q_4$ and $q_5$ can be determined exactly, the prediction will be precise. However, the dynamic speed of each vehicle can’t be determined exactly in microcosmic in practice, i.e. we can’t validate the travel time of each vehicle. The factors that influence $q_0$ conceptually fall into two categories: deterministic and uncertain. Deterministic factors contain the traffic volume of upstream at a validated interval ($q_{1S}$, $q_{2R}$, $q_{3L}$, $q_4$ and $q_5$); uncertain factors are comprised of the microcosmic dynamic speed and travel time. Previous traffic forecasting methods usually provide the information to strategic road panning based on data which statistical interval and prognosis horizon are monthly or yearly. In contrast, short-term prediction often has a prognosis horizon of only a few minutes for traffic management and route guidance. The prognosis horizon decides the statistical interval of traffic flow, i.e. short-term term traffic prediction needs short statistical interval (the maximum interval must less than the prognosis horizon). Therefore, more detailed road information would be
provided in the outcome of prediction, on the other hand the more random events and noisy would be emerge in short-term prediction, and consequentially the more errors in the prediction because the more dimensions of the microcosmic complex traffic system.

2.2 Errors from noise and chaos

When we analyse the time series of traffic volume, its noise and chaos characteristic are very important factors that should be considered. Analysing the noise and chaos is available to prompt the prediction precision. Noise cannot be predicted; only a range probability could be given to describe the changes of noise time series. In practice, we’d better to separate the noise from the traffic flow time series, and validate the characteristics of the noise (such as mean and var). As for chaos, the form of chaos time series is unorganised and noisy superficially, however, chaos is essentially orderly, indiscernible inasmuch as it is there, but has to be searched for.

The prediction errors may fall into two categories: measurement and model. The error causing from measurement is inevitable. The model errors always derive from the absence of essential parameters or the necessary principle characters of data (such as chaos). If the data has chaos or fractal characteristics, parameters of the multi dimensions and proper delay time are needed to make the model match the real traffic system. How to minimize the prediction errors would be discussed in section 3.

3 An improved combined method

3.1 The “hysteresis” phenomenon

In the prediction of previous literatures, the “hysteresis” phenomenon always companions the prediction error such as the results in reference [12,13].

This is because the prediction is based on the contiguous change trends of the time series i.e. only the adjacent data of the prediction time points without considering the periodic and fractal factors. However, inadequate evolvement of the recent change trends could be found in the time-delay recurrent model and fractal self-similar model, which can predict the coming of the cusp catastrophes but always early such as the results in reference [2, 10].

Fractal self-similar model and time-delay recurrent model have considered more inbeing characteristic (such as period, chaos and fractal) of short-term traffic time series therefore they could forecast the coming of the cusp catastrophe in the traffic flow dynamic curve i.e. the congestion of the road. This bases on analysing large amount of available historical short-term traffic flow data. However, the cusp catastrophes of the predictions always come early than the real data. This finding illuminates us to find an improved method of the combination ANN and fractal self-similar model to counterbalance the errors of respective model, and use linear model, ANN or Kalman filter model approaches to match the changes of combination parameters which to counteract the multi-model errors.
3.2 Data analysing

The data was collected from the highway from Guangzhou to Foshan. There two step in data analyzing: Hurst exponent analyses, chaos and fractal characteristics analyzing.

3.2.1 Hurst exponent analyses

The value of the Hurst exponent is within the range of 0 and 1. When the Hurst exponent value is 0.5, the time-series data follows a random walk that is typically unpredictable data, while Hurst exponent=1 indicates a complete linear movement and Hurst exponent=0 represents a complete flip-flop movement between two consecutive periods, and Hurst exponent=0 represents a complete flip-flop movement between two consecutive periods. The Hurst exponent of the real data is 0.32. This means the data is predictable.

3.2.2 Chaos and fractal characteristics analysing

Take proposed the original theory of the phase reconstruction of time series. The evolution of the systemic variable was correlated other variables which effect them reciprocally, and the information form these mutual variables was kept in the developing process of any variable. Therefore, we only need one variable to expand at some deferred points of fixed time to reconstruct a status space. Grassberger and Procaccia have proposed the concrete algorithm (G-P algorithm) of the phase reconstruction [10, 11, 14]. (See the results of real data in Table 1)

Table 1: Correlation dimension of the validated embedded dimension and statistical interval of the traffic flow time series.

<table>
<thead>
<tr>
<th>Embedded dimension</th>
<th>1 Min.</th>
<th>5 Min.</th>
<th>15 Min.</th>
</tr>
</thead>
<tbody>
<tr>
<td>M=6</td>
<td>-</td>
<td>-</td>
<td>1.1971</td>
</tr>
<tr>
<td>M=7</td>
<td>-</td>
<td>1.3336</td>
<td>1.2456</td>
</tr>
<tr>
<td>M=8</td>
<td>1.6616</td>
<td>1.3793</td>
<td>1.2892</td>
</tr>
<tr>
<td>M=9</td>
<td>1.6918</td>
<td>1.4204</td>
<td>1.3077</td>
</tr>
<tr>
<td>M=11</td>
<td>1.7447</td>
<td>1.4899</td>
<td>1.3103</td>
</tr>
</tbody>
</table>

From Fig.6 and Table.1 we can find that the short-term traffic time series is obviously chaos and fractal when the statistical interval is the 5min or 15min. However, when the statistical interval is 1min, the embedded dimension is more than 8, and the fractal characteristic is obscure. The reason is the chaos and fractal characteristics of traffic flow time series are based on limited range of statistical interval. When the statistical interval is less, the changes of traffic flow are more random and complex therefore needed more (probably $\infty$) variables to describe the system status.
3.3 The combine prediction method

The proposed method is established on the basis of three sections: prediction based on fractal self-similar and ANN approach method, prediction based on wavelet resolve-reconstructs and ANN approach of the resolved sub-series method, the last is combining two above models with proper parameters.

3.3.1 Fractal self-similar and ANN method based on real data

Firstly, with respect to the G-P algorithm outcome of the real data, selects the delay time $\tau = 1$, dimension of the reconstruction phase $m = 6$, we can reconstruct the phase of the short-term traffic time series. Furthermore, using RBF neural network approach to match the curves of the phase track.

In order to evaluate the precision of method, four error indices are used in this paper: mean absolute error (MAE), mean square error (MSE), mean absolute percent error (MAPE) and mean square percent error (MSPE). Where:

$y_t$ is the real data;
$\hat{y}_t$ is the prediction value;

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_t - \hat{y}_t|;$$

(1)

$$\text{MSE} = \frac{1}{n} \sqrt{\sum_{i=1}^{n} (y_t - \hat{y}_t)^2};$$

(2)

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|;$$

(3)

$$\text{MSPE} = \frac{1}{n} \sqrt{\sum_{i=1}^{n} \left( \frac{y_t - \hat{y}_t}{y_t} \right)^2}.$$

(4)

The prediction is shown in the following Fig 2 and Table 2. We can find the prediction can predict the changes of traffic flow curve previously, however not very precisely.

![Figure 2: Forecasting based on fractal self-similar and RBF model.](image)
Table 2: Error index of fractal self-similar and RBF model.

<table>
<thead>
<tr>
<th>Error index</th>
<th>MAE</th>
<th>MSE</th>
<th>MAPE</th>
<th>MSPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-similar and RBF model</td>
<td>15.0833</td>
<td>4.9575</td>
<td>0.1236</td>
<td>0.0402</td>
</tr>
</tbody>
</table>

Table 3: Error index of B-P neural network model.

<table>
<thead>
<tr>
<th>Error index</th>
<th>MAE</th>
<th>MSE</th>
<th>MAPE</th>
<th>MSPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-P neural network model</td>
<td>11.9167</td>
<td>4.7118</td>
<td>0.1114</td>
<td>0.0464</td>
</tr>
</tbody>
</table>

Figure 3: Prediction of the two models.

3.3.2 Prediction based on BP neural network model
This model needs to count self-correlation value of the time series in order to validate the nodes of the input layer. The detail algorithm can be referred with [10].

As shown in Fig 8, the self-correlation value \( C \) of the real data is 1.4. Furthermore the reconstruction dimensions \( D \geq 2C+1 \), so the nodes of input layer are 4 or more. In this paper, we select 6 nodes as the input layer. The prediction of B-P neural network is shown in Fig 3 and Table 3.

3.3.3 Combination of the two models
In this section we minimize the “hysteresis” phenomenon in order to improve the precision of the prediction by analysing errors of different models and combining the two models. This section comprises two steps: amendment of perspective method errors, weight validation of perspective method (combination).

3.3.3.1 Amendment of perspective method errors
The prediction error of each step constructs a time series, so we can predict the next step error based on analysing model error time series, and re-evaluating the prediction of traffic volume based on the error prediction.

\[
\frac{\dot{x}(t) - x(t)}{x(t)} = m(t) ;
\]  
(5)
\[\therefore \hat{x}(t) = [m(t) + 1]x(t) \quad (6)\]
\[\therefore \hat{x}(t + 1) = \left[\hat{m}(t + 1) + 1\right]x(t + 1) \quad (7)\]

where:
\(\hat{x}(t)\): Prediction value of traffic time series at step \(t\);
\(x(t)\): Real data at step \(t\);
\(\hat{x}(t + 1)\): Amendatory prediction value of \(\hat{x}(t)\) based on re-evaluation at step \((t+1)\);
\(\hat{m}(t + 1)\): Prediction of the model error at step \((t+1)\).

Considering the limited data, in this paper we re-evaluate the last two prediction traffic values. Using linear model approach matches the model error time series.

### 3.3.3.2 Weight validation of perspective method

We expect proper weights of the perspective model to construct an improved combination. So, here we introduce the error variance \(n_i(t) \cdot (\hat{x}(t) - x(t))\) of the \(i\) model at \(t\) step, in this paper \(n_i(t)\) is relate to the Fractal self-similar model and \(n_j(t)\) relates the B-P neural network model. \(n(t)\) (the model error) is a time series, and we could use proper linear or non-linear approaches (such as AR, ARIMA, ANN and Kalman filter model) to match its change, here we use AR model. Therefore we can combine two models with the following formula.

\[
\hat{x}(t + 1) = \frac{\hat{x}_i(t + 1)(\hat{n}_j(t + 1))^2 + \hat{x}_j(t + 1)(\hat{n}_i(t + 1))^2}{(\hat{n}_i(t + 1))^2 + (\hat{n}_j(t + 1))^2} \quad (8)
\]

\(\hat{x}(t + 1)\): Prediction of combination model at time \((t+1)\);
\(\hat{x}_i(t + 1)\): Prediction of Fractal self-similar model at time \((t+1)\);
\(\hat{x}_j(t + 1)\): Prediction of BP neural network model at time \((t+1)\);
\(\hat{n}_i(t + 1)\): Error \((n_i(t))\) estimation of Fractal self-similar model at time \((t+1)\);
\(\hat{n}_j(t + 1)\): Error \((n_j(t))\) estimation of BP neural network model at time \((t+1)\);
The re-evaluate predictions of combination model and its error indices are shown in Table 4.

Table 4: Prediction and error indices of improved combination model

<table>
<thead>
<tr>
<th>Error index</th>
<th>Real data</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>102</td>
<td>110</td>
</tr>
<tr>
<td>MSE</td>
<td>9</td>
<td>6.8</td>
</tr>
<tr>
<td>MAPE</td>
<td>0.0977</td>
<td>0.0704</td>
</tr>
<tr>
<td>MSPE</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

4 Summary and outlook

In this research, we propose an improved method based on analysing and re-evaluating errors of perspective model and a combination model. The detailed process is shown in the following Fig.4. Only one model is difficult to describe the full-scale characters of short-term traffic flow time series, the improved method in this paper can help us to combine different models in order to get precise prediction of short-term traffic by extracting the different characters of traffic flow time series in long or short statistical intervals.

Step 1: Data analyse

Step 2: Select proper models (Model-1, model-2, … model-n)

Step 3: Error prediction of perspective model based on analyzing time series of error index \( m(t) \), and re-evaluate the prediction of perspective model.

Step 4: Combination model based on prediction of error index \( n(t) \), and re-evaluate the prediction of traffic flow.

Figure 4: The process of short-term traffic prediction.

The research of cusp catastrophe of short-term traffic flow volume theory will be helpful to the prediction of short-term traffic flow. As we know, the traffic volume is limited with the road capacity, and this is exhibited at the maximal cusp. Furthermore, the prediction of cusp catastrophe will tell us the becoming of congestion or traffic accident. Therefore, we’d better to concentrate effort on researching prediction cusp catastrophe of short-term traffic flow in the future.
Acknowledgements

This research was supported by NSFC grant 70371022, 50338030 and 50378042 funds.

References