Multi-time Scale Traffic Flow Prediction Method for Peak Tourist Seasons and Its Application: Postprint

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Abstract

Tourism traffic during peak periods triggers a surge in traffic demand, alters the spatiotemporal distribution patterns of normal traffic, and influences travelers' behavior. Accurate short-term prediction of tourism traffic demand is extremely challenging, and its spatiotemporal distribution patterns are even more difficult to estimate. To address this issue and improve prediction accuracy, this study first analyzes the multi-timescale predictability of tourism traffic flow, and subsequently employs multi-timescale prediction methods to forecast tourism traffic volume. The results demonstrate that the model exhibits favorable predictive performance and high accuracy. Constructing a multi-timescale tourism traffic prediction model from classification and hierarchical perspectives, analyzing tourism traffic flow distribution and dynamic allocation of tourism traffic flow, can provide an accurate reference for rapid assessment of road traffic operational status during tourism peak periods and for formulating emergency traffic organization and management schemes.

Full Text

Preamble

Multi-Time Scale Prediction Method and Application on Tourism Fastigium Traffic Flow

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Abstract: Peak tourist traffic leads to sharp increases in traffic demand, alters the temporal and spatial distribution patterns of normal traffic, and influences traveler behavior. Accurate short-term prediction of tourism traffic demand is extremely difficult, and its spatiotemporal distribution patterns are even harder to estimate. To address this challenge and improve prediction accuracy, this paper first analyzes the multi-time scale predictability of tourism traffic flow, then applies a multi-time scale forecasting method to predict tourism traffic volume. Results demonstrate that the model exhibits good predictive performance and high accuracy. Constructing a multi-time scale prediction model for tourism traffic from classification and stratification perspectives, and analyzing the distribution and dynamic allocation of tourism traffic flow, provides a precise reference for rapid assessment of road traffic operation conditions during peak travel seasons and for formulating emergency traffic organization and management plans.

Keywords: tourism fastigium; traffic flow forecasting; predictability; multi-time scale

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0 Introduction

The tourism transportation system is a complex system. A persistent research focus in tourism transportation science concerns how to ensure smooth, comfortable, and efficient tourist activities through technological upgrades based on existing tourism transportation infrastructure in tourist cities [1,2]. Currently, urban transportation problems in China are increasingly severe, with traffic congestion, frequent accidents, and exhaust pollution constraining the sustainable development of urban tourism [3]. In tourism transportation environments, these normalized urban traffic problems are further amplified, seriously affecting tourists' normal travel needs, reducing tourism efficiency, and potentially triggering mass incidents that impact social stability [4].

Therefore, accurately grasping and predicting tourism traffic flow is crucial for advance traffic organization and management, ensuring smooth traffic, improving tourism transportation service quality, and maximizing tourists' time benefits. Real-time, accurate short-term traffic prediction data supports various functions in tourism traffic management, including multi-mode optimal path optimization, dynamic impedance calculation, and road traffic state discrimination. Numerous methods and models currently exist for short-term traffic flow prediction [5], with substantial research both domestically and internationally [6,7]. These include linear models, nonlinear models, and hybrid models, employing methods such as moving average, exponential smoothing, fuzzy control, search engine-based approaches, grey theory, convolutional neural networks, particle swarm optimization, and support vector machines [8~11]. Time series prediction models are relatively mature and offer good advantages for short-term forecasting. Many scholars have improved upon basic time series models; for example, Tang et al. [12] used time series models to predict short-term highway traffic flow, focusing on dynamic parameter adjustment. Yao et al. [13] analyzed multi-point time series prediction methods, while Tian et al. [14] combined time series data models with BP neural networks. Overall, although current models and methods have improved upon basic models, most support only single-time-scale prediction and inadequately consider the characteristics, differences, and predictability of traffic information across different time scales, resulting in significant errors and instability. To address these issues, this paper focuses on multi-time scale prediction technology for traffic flow on road segments with detectors to improve the accuracy of tourism traffic flow prediction.

1 Multi-Time Scale Predictability Analysis of Tourism Traffic Flow

In the current big data era, diverse information prediction methods share the common core of using mathematical approaches to process sample data. Achieving good prediction results requires not only selecting prediction methods that match the characteristics of sample data sequences and ensuring sufficient sample data, but also that the sample data sequences themselves possess good predictability—that is, they exhibit certain statistical regularities rather than being completely random. Therefore, the premise for multi-time scale prediction of dynamic traffic flow information is determining that real-time dynamic traffic flow parameters are inherently predictable.

1.1 Characteristics Analysis of Tourism Traffic Flow

1) Complexity of Tourism Traffic Flow

Compared with highways, urban road traffic flow, particularly in tourist city scenic areas, exhibits significant differences. Highways are fully enclosed, fully grade-separated, and access-controlled, with relatively few ramp-controlled entrances and exits, enabling stable and controllable driving speeds. In contrast, urban roads form a network structure of points and lines, with multiple entrances and exits on single road segments, including expressways, arterial roads, secondary roads, and branch roads that interconnect, making driving speeds difficult to control. Highway vehicles rarely change lanes and travel in a single direction, whereas urban road traffic frequently changes lanes and overtakes, with diverse traffic flow directions and free route choices. Without accidents, highway traffic flow rarely experiences delays, while urban network traffic constantly stops and starts due to numerous signalized intersections [15]. Additionally, urban road networks are dense, numerous, and bear enormous traffic volumes, with non-uniform geometric conditions due to urban layout; they suffer from severe morning and evening peak congestion; and face numerous interference factors such as pedestrians, bicycle crossings, and bus stops—especially since scenic area traffic flow is significantly affected by tourist volumes. Urban roads also feature left-turn, through, and right-turn exclusive lanes. These characteristics make predicting tourism road traffic flow parameters more difficult, with challenging model selection and lower prediction accuracy.

2) Multi-Time Scale Traffic Flow Characteristics Analysis

To explore tourism traffic flow characteristics across different time scales, we analyzed the predictability of traffic parameters on a coastal avenue wildlife park road segment in a major tourist city at multiple time scales. We investigated 24-hour traffic flow data on the main direction of the coastal avenue. First, we plotted all-day traffic flow curves with time scales of 1 hour, 15 minutes, 3 signal cycles, and 1 signal cycle as the horizontal axis and hourly traffic volume as the vertical axis, as shown in [Figure 1: see original paper]. As the time scale shortens progressively across the four curves, the randomness of traffic flow data increases, with enhanced discreteness and volatility. Second, we compared traffic data from the same day across three weeks, evaluating variance, extreme values, and skewness of the time series data. We found that the first three time scales exhibited certain statistical characteristics, while the 1-signal-cycle time scale showed no statistical characteristics, indicating that statistical analysis methods struggle to complete short-term traffic parameter prediction.

1.2 Multi-Time Scale Predictability Analysis of Tourism Traffic Flow

Traffic flow predictability can be determined through flow recurrence plots at different observation scales [19]. By analyzing line segments parallel to the main diagonal in recurrence plots and statistically examining their lengths and densities, we can precisely determine whether tourism traffic flow time series data is predictable at different time scales. Longer and denser line segments parallel to the main diagonal indicate better data convergence, good predictability, and high prediction accuracy; conversely, they indicate high divergence, poor predictability, and unreliable prediction accuracy.

[Figure 2: see original paper] and [Figure 3: see original paper] show flow recurrence plots for the main road in this tourist city. The quasi-periodic sequence (5-minute time series in [Figure 2: see original paper]) exhibits relatively long and dense line segments parallel to the main diagonal, demonstrating good predictability at the 5-minute time scale because this exceeds one signal cycle, giving traffic flow regularity. The chaotic sequence (1-minute time series in [Figure 3: see original paper]) shows short and sparse line segments parallel to the main diagonal, indicating poor predictability at the 1-minute time scale because this is shorter than one signal cycle, making traffic flow discrete.

In summary, urban tourism traffic flow data are clearly time series data with certain regularities and correlations, possessing predictability at different time scales. Based on similarity search concepts and historical traffic flow data from different times and spaces, this paper designs a method to search for data sequences with maximum similarity to future traffic characteristics, combining current real-time data to propose a multi-time scale prediction method for urban road tourism traffic flow.

2 Multi-Time Scale Prediction Method for Urban Road Tourism Traffic Flow

Currently, main road sections in major tourist cities are equipped with traffic information detection devices such as video detectors and inductive loop detectors, making traffic flow (particularly vehicle arrival rates at intersections) measurable [20]. Various short-term traffic flow prediction methods have emerged under these conditions, using known traffic flow parameters from several unit periods to predict trends in the next unit period through information processing techniques like weighted averaging, Kalman filtering, and neural networks. Tourism traffic management functions—including multi-mode optimal path optimization, dynamic impedance calculation, and road traffic state discrimination—have different time scale requirements for traffic prediction data (generally 1 minute, 5 minutes, and 15 minutes, respectively). Predicting only the next unit period' s traffic flow parameters is insufficient; simultaneous prediction of multiple future traffic flow parameters is required.

2.1 Multi-Time Scale Prediction Model for Urban Road Tourism Traffic Flow

1) Time Series Characteristics of Urban Road Tourism Traffic Flow Data

In urban networks, traffic behavior is spatiotemporally continuous, and dynamic traffic flow parameters possess all characteristics of time series data with particular special features. This paper analyzes the special characteristics of dynamic traffic flow parameters to select appropriate data mining methods.

a) Spatiotemporal Correlation

Dynamic traffic flow parameters exhibit both temporal and spatial correlation. The former manifests as time correlation of flow data at the same location and time period on the same weekday or non-weekday, a characteristic made more obvious by traffic demand control measures like vehicle restrictions in tourist cities. The latter appears as strong delayed spatial correlation of traffic flow data on upstream and downstream road segments at the same intersection.

b) Trend Consistency from Intersection Phase Coordination Design

Motor vehicle and non-motor vehicle flows in the same direction should be arranged in the same phase as much as possible, with phase green time determined by balancing their flow volumes. When flow distribution is unbalanced across directions, signal phases can be terminated early or started late to control non-motor vehicle flows, with green time constraints on signal phases to ensure non-motor vehicle safety. Conflicts between motor and non-motor vehicle flows should be avoided, and green signal start times for motor vehicles, non-motor vehicles, and pedestrians in the same direction should be consistent. These measures ensure roughly balanced distribution of traffic flows in the same direction at network nodes.

c) Trend Consistency from Phase Design for Different Flows at the

Same Approach
Ensuring continuity of phases along the same traffic flow line; determining reasonable vehicle flow combinations based on intersection flow distribution characteristics and considering crossing conflicts of non-motor vehicle flows at intersections; coordinating non-motor vehicle left-turn passage with left-turn exclusive phase settings based on left-turn motor vehicle and non-motor vehicle flow proportions; and emphasizing the impact of right-turn flows on other flows and pedestrians at exits, setting right-turn exclusive phases when necessary. These measures ensure roughly balanced distribution of different directional traffic flows at network nodes [21].

2) Establishment of Prediction Equations
Basic parameter definitions for the prediction equation are as follows:

a) Define $Q = \{q_1, q_2, \dots, q_t\}$ as the real-time traffic flow parameter time series collected by detectors on the current day, where $q_1, q_2, \dots, q_t$ represent parameter values for periods $1, 2, \dots, t$, with each period' s time interval depending on sensor data collection granularity or manually determined according to application functions, and t representing the current period.

b) Define $Q_B = \{Q_1, Q_2, \dots, Q_M\}$ as the historical database collection of traffic flow parameter time series, where M represents the number of time series data in the historical database.

c) Define $Q' = \{q'_1, q'_2, \dots, q'_t, \dots\}$ as the time series data with maximum similarity to Q searched from Q_B.

d) Define $Q_C = \{q_1, q_2, \dots, q_t, q'_{t+1}, q'_{t+2}, \dots\}$ as the data development sequence of Q.

Since traffic behavior and environments change randomly in real time, actual traffic systems are typical complex systems. Even for the same spatiotemporal target, two completely identical time series cannot appear, meaning Q and Q' cannot have completely consistent data values and development patterns. Q' must be constantly corrected based on measured data to reduce prediction error. The specific approach is:

a) Apply exponential smoothing to predict $\hat{q}_{t+1}$ (traffic flow parameter prediction at time $t+1$) using Q and q'_{t+1} as shown in Equation (1).

b) Similarly predict $\hat{q}_{t+2}$.

c) Finally obtain $\hat{Q} = \{\hat{q}_{t+1}, \hat{q}_{t+2}, \dots, \hat{q}_{t+N}\}$ and output prediction results.

Where α is the exponential smoothing parameter, with $0 < \alpha < 1$.

Summarizing the above process yields the urban road tourism traffic flow multi-time scale prediction flowchart shown in [Figure 4: see original paper].

3) Determination of Maximum Time Scale
Theoretically, prediction steps cannot increase without limit. Assuming a data

collection time granularity of 5 minutes, using 12:00 data to predict 12:05, 12:10, and 12:15 is reasonable. As steps increase, prediction error grows, and using it to predict larger time intervals (e.g., 12:50) may lose reasonableness—obviously, 12:50 data would be more reasonably predicted using 12:45 data. Therefore, for multi-time scale prediction, there must exist a maximum time scale corresponding to the maximum prediction steps.

Assume N is the prediction step number corresponding to the maximum time scale. Its reasonable value can be determined by:

a) **Function-based Fixed-Scale Method**: Since tourism traffic management functions like multi-mode optimal path optimization, dynamic impedance calculation, and road traffic state discrimination have different implementation methods and time scale requirements for traffic flow prediction data, the maximum time scale can be determined according to specific application functions.

b) **Data-based Variable-Scale Method**: Calculate the cumulative similarity between current traffic flow time series data and historical time series data to dynamically adjust the maximum time scale. Greater similarity allows forward adjustment of the time scale, with adjustment amount depending on the maximum error acceptable to the function.

2.2 Similar Sequence Search Method

To ensure successful implementation of the prediction model, an effective similar sequence search method must be designed to quickly and accurately find data sequences matching the prediction target, enabling precise tourism traffic flow prediction based on the multi-time scale prediction model. Key aspects include expression patterns, similarity calculation, and similarity search for traffic flow time series data.

1) Expression Patterns for Traffic Flow Time Series Data
Existing literature includes symbolic patterns, frequency domain patterns, singular value patterns, and piecewise linear patterns [16~18]. Comparing these patterns' advantages and disadvantages, and considering the spatiotemporal attributes of traffic flow data and the need for real-time search, this paper selects piecewise linear pattern as the expression pattern for traffic flow time series data.

Time series piecewise linear representation can also be directly expressed through flow recurrence plots. The core of this pattern is reasonably selecting the number of line segments K to maximally preserve original time series data characteristics. Excessive K values increase subsequent algorithm complexity geometrically, while too small values severely affect similarity search accuracy. This paper uses "marker point technology" to determine K:

a) Determine first-order marker points of time series data. If time series S contains n points and S values are functions of time, then S can be expressed as $S(t)$, $t = 1, 2, 3, ...$, where S is time series data as a time variable function; S_t is a data point at time t; and t_i is a first-order marker point defined as $(t_i, y(t_i))$.

b) Determine line segment slope. From step a), two adjacent marker points determine a line segment and its slope: $\alpha_i = (y(t_{i+1}) - y(t_i))/(t_{i+1} - t_i)$.

c) Error estimation. The cumulative error of the entire line segment depends on relative errors between each data point within the segment and true values: $B_i = \sum_{j=1}^{M} \beta_j^2$, where B_i is line segment cumulative error; $\{\beta_j, j = 1, 2, \dots, M\}$ is the set of relative errors between each data point and true values; and M is the number of data points.

2) Similarity Calculation for Traffic Flow Time Series Data

Similarity between traffic flow time series data can be quantified as similarity distance. After piecewise linearization, a traffic flow time series is equivalent to a set of connected line segments with intersection points defined as breakpoints. Assuming S is the linear segmentation result of a traffic flow time series containing four variables with K segments: $S \equiv \{STL, STR, SYL, SYR\}$, where STL, STR are time markers (start/end times of the i-th line segment in S) and SYL, SYR are value markers (traffic flow data at line segment start/end points). The similarity distance between two time series is calculated through comparative analysis of these markers.

3) Similarity Search for Traffic Flow Time Series Data

Due to external conditions like power, communication, and climate, tourism traffic flow data collection often experiences loss and distortion, making historical time series data incompletely continuous or authentic. Therefore, when searching historical databases based on current traffic flow time series, the core objective is finding historical data sequences with maximum similarity to the target sequence within the same time period for multi-time scale prediction of next-period traffic flow trends. Several details require attention:

a) Search Real-Time Performance

The purpose of tourism traffic flow time series similarity search is to quickly and accurately find time series data with highest similarity to current traffic flow from the historical database. The enormous historical data volume makes exhaustive search complex and time-consuming, preventing real-time traffic flow prediction. Therefore, graph theory' s layering and partitioning concepts can divide the historical database into subsets by time and space attributes. Searching first by attribute to determine subsets, then exhaustively searching within subsets, greatly improves speed. To further enhance real-time performance, truncation rules can be set: determine reasonable similarity distance thresholds—when a sequence with similarity distance below the threshold is found, stop searching and output results; simultaneously determine reasonable search time thresholds—when search time exceeds the threshold, stop searching and output the most similar sequence found.

b) Time Interval Conversion Between Measured and Historical Data
In tourism traffic systems, different functional traffic information sensors have different data collection time granularities. For example, inductive loops typically collect data every 3-5 seconds, while video detectors recognize images every 5-15 seconds. However, historical databases generally use longer storage intervals (at least >10 minutes) for storage space and data usage considerations. Therefore, real-time data must be converted to the same time interval as historical stored data before similarity search.

c) Reasonable Time Interval for Similarity Search
Currently, traffic parameter prediction is generally short-term. Since exhaustive similarity search in historical databases requires time while sensor sampling time granularities are short, searching all samples is impossible and unnecessary because adjacent sensor data generally changes little. However, excessively long intervals cause cumulative errors in previous period similarity search results. Therefore, to ensure both prediction accuracy and model real-time performance, the time interval for similarity search must be reasonably determined. Based on tourism traffic characteristics analyzed earlier, this interval should be no less than 15 minutes.

2.3 Performance Evaluation Method for Prediction Model

The tourism peak period scenic area surrounding road traffic flow parameter prediction model established in this paper is a microscopic model requiring high data prediction accuracy; otherwise, it affects emergency traffic management control strategy implementation. Accuracy primarily reflects error between model predictions and real data. Absolute error measures the gap between actual and predicted values, while relative error reflects the percentage of absolute error relative to predicted values, better indicating model credibility. For the tourism traffic flow prediction model, absolute and relative error calculations best fit precision testing. Equation (9) shows absolute error calculation, Equation (10) shows relative error calculation:

$$SA(t) = |y(t) - \hat{y}(t)|$$

$$SR(t) = \frac{|y(t) - \hat{y}(t)|}{y(t)}$$

Where $SA(t)$ is absolute prediction error at time t; $SR(t)$ is relative prediction error at time t; $y(t)$ is actual traffic flow data uploaded by detectors at time t; and $\hat{y}(t)$ is model output traffic flow prediction at time t.

In this prediction model, traffic flow parameter prediction for a specific road segment at a specific moment is multi-time scale. Assuming prediction steps of n, the model simultaneously outputs n predicted data: $\hat{y}_{t+1}, \hat{y}_{t+2}, \dots, \hat{y}_{t+n}$. To accurately evaluate multi-step prediction comprehensive effects, average absolute and relative errors of the n predictions are calculated as final error metrics:

$$MSA(t) = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

$$MSR(t) = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i}$$

Where $MSA(t)$ is multi-time scale average absolute prediction error at time t; $MSR(t)$ is multi-time scale average relative prediction error at time t; and y_i is actual traffic flow data uploaded by detectors at time t.

3 Case Study

This paper uses actual data to test the urban road traffic flow parameter multi-time scale prediction method. Data were collected from a tourist city' s main tourism road, selecting a 7.66 km experimental road segment with 15 data collection points (through continuous video recording and subsequent image processing for flow data collection). Average spacing between collection points was 0.5 km, with flow data statistics processed at 2-second granularity during post-processing. Sampling period was June 3-8, 2015.

Data collection point No. 008 was randomly selected as the analysis target. Due to technical limitations of video detector image processing, the original data sequence contained discontinuities and obvious anomalies. Quality evaluation and control were performed on the original data sequence, including data repair and smoothing operations, to complete standardized processing of continuous time series data, with results shown in [Figure 5: see original paper].

Using No. 008 collection point' s June 3, 2015 flow time series data as the target, the similar sequence search method constructed in Section 2.2 was applied to search for similar sequences from the historical database, and prediction was completed using the model established in Section 2.1. Specific steps:

a) Standardize June 3's raw flow time series data, then represent the standardized data through piecewise linearization, with processing results shown in [Figure 6: see original paper].

b) Obtain geometric coordinates of 10 segmentation points from [Figure 6: see original paper], extract flow data corresponding to the 10 breakpoint coordinates from other days in the historical database, calculate piecewise similarity between historical and current day data, and accumulate piecewise similarity results to obtain cumulative similarity data, with calculation results shown in .

In , using the June 3-8 data column as an example, value 0.047 represents the piecewise similarity distance between June 3 and June 8 breakpoint data at 11:00 AM; value 0.116 represents the cumulative sum of piecewise similarity distances between June 3 and June 8 traffic flow time series data from midnight to 11:00 AM. Smaller values indicate higher similarity.

c) For visualization, Excel was used to create piecewise and cumulative similarity distance variation curves between sample data time series, shown in [Figure 7: see original paper] and [Figure 8: see original paper].

d) According to the multi-time scale prediction method flowchart in [Figure 4: see original paper], multi-time scale prediction of future traffic flow data for detection point 008 on June 3 was performed, with 15-minute time scale selected for error demonstration. Comparison between predicted and measured values is shown in [Figure 9: see original paper].

Absolute and relative errors between 15-minute time scale predictions and real values were calculated, shown in . The last row shows that the urban road tourism traffic flow multi-time scale prediction method achieved an average absolute error of 16.8 vehicles and average relative error of 12.8% at the 15-minute time scale, with accuracy fully meeting tourism peak period traffic management system application requirements.

4 Conclusion

Combining specific characteristics of tourism traffic demand, this paper analyzed tourism traffic prediction methods. Based on confirming the predictability of tourism peak period traffic flow time series data, a similarity search method based on historical time series data was proposed, an urban road tourism traffic flow multi-time scale prediction model was established, and model performance was evaluated. Actual measured traffic data from scenic area roads in a real region were used to verify the proposed prediction model' s accuracy.

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Note: Figure translations are in progress. See original paper for figures.