

An Evaluation Model of Traffic Abnormal Probability of Adjacent Freeway Nodes Based on Space-time Constraints

Jun Guo*, Xinwei Liu*, Chen Liu**, Zixuan Zhao***, Bin Zhang*

*Software College, Northeastern University, Shenyang Liaoning Province China

**School of Computer Science and Engineering, Northeastern University, Shenyang Liaoning Province China

***School of metallurgy, Northeastern University, Shenyang Liaoning Province China

guojun@mail.neu.edu.cn, liuxinwei96@outlook.com, liuchen@cse.neu.edu.cn, 1011282890@qq.com, zhangbin@mail.neu.edu.cn.

Abstract—At present, as an important transportation way of citizens and resources, motorway is of great significance to people's life development. However, heavy traffic while increases risks of traffic anomalies while bringing prosperity. In view of the above problems, this paper proposes a method for analyzing the probability of traffic abnormalities based on the space-time constraints, and establishes a probability evaluation model for traffic abnormalities between adjacent nodes of motorway. Firstly, the average arrival time of the traffic flow at adjacent nodes based on the morphological similarity distance is calculated, and then Augment Dickey-Fuller is applied to judge whether the traffic-flow difference sequence between adjacent nodes is stable. For those with unstable difference sequence, the probability of traffic abnormality shall be calculated. If the probability value is greater than the set threshold, it shall be regarded as traffic abnormality. And the feasibility of the proposed method is proved by the experimental results. Therefore, the probability estimation model of traffic anomalies at adjacent nodes of motorways based on space-time constraint can be used to evaluate traffic anomalies of motorways.

Keywords— traffic flow; traffic abnormality; space-time constraints; morphological similarity distance; Augment Dickey-Fuller;

I. INTRODUCTION

With the deepening of economic globalization and China's accelerating process of urbanization & industrialization, the motorways are experiencing a stage of rapid development. The number of private cars and buses on the road is increasing rapidly, which intensifies traffic congestion, vehicle collision and other abnormal traffic problems. In developing countries, one person dies in traffic accidents every four minutes^[1]. Therefore, a set of intelligent transportation system is essential, through which traffic conditions (such as retrogradation behavior of vehicles^[2], collision behavior of vehicles^[3]) are monitored, and a large quantity of traffic data (such as the speed change^[4], traffic flow states^[5]) are analyzed, to manage the vehicle, reduce the pressure of road travel, minimize the loss caused by abnormal traffic and reduce the potential safety hazard. During the detection and analysis of traffic anomalies, Murat Ozbayoglu etc. put forward a

preliminary real-time autonomous accident-detection system based on computational intelligence technology, which applied big- data processing method to integrate the data, and combined the data from the sensor with the event log, so as to extract the most appropriate features for the incident detection model. Then, three different accident detection & computation Intelligence models, including nearest neighbor, regression tree and feed-forward neural network were constructed^[6]. Yu Yao et al. proposed an unsupervised method for traffic-accident detection in first-person video, by which the generated antagonistic network was applied to detect vehicles and tracking vehicles, and the position of vehicles in the next few frames and the size of the deviation from the actual position were estimated to calculate the probability of traffic accidents^[7]. Nejdet Dogru et al proposed an intelligent detection system for traffic incident to equip the vehicle with V2V communication equipment. In addition, vehicles exchanged the vehicle speed and coordinate between each other. Three kinds of machine learning model were applied, including artificial neural networks (ANNs), support vector machines (SVMs) and random forest (RFs), so as to establish classification model of accident cases and normal cases^[8]. Rupam Deb et al. proposed a noise-based classifier algorithm to identify and correct noise attribute values in large data sets of traffic accident and to improve the detection accuracy for traffic accident^[9]. ChihJung Lee et al. proposed an audio-based early warning system for vehicle approaching events. In this system, the microphone collected sound signals and extracts sound features, then used various methods, such as K-nearest neighbor and decision tree, to classify the audio, thus determining whether there is a car or not and increasing the passerby's safety^[10]. Joan Claudi Socoró designed a detector for abnormal noise event based on a distributed low-cost acoustic sensor, which was used to distinguish road traffic noise and abnormal noise events in real time within a predetermined time interval. In his paper, the standard Meir cepstrum coefficient and Gaussian mixture model were used for classification^[11]. Rosa Maria Alsina-Pagès et al. collected road traffic sounds through the wireless sound sensor network, and classified the event types of events (birdsong, thunder, music, etc.) unrelated to road traffic noise

(alarm, horn, etc.) through time of duration, signal-to-noise ratio and other characteristics [12,13]. Bhandarkar M et al. analyzed the different spectrum content contained in the accumulated signals of noise generated by various parts of the vehicle, used support vector machines and artificial neural network classifiers to determine different traffic density states, and divided the traffic flow state into congestion (0-10km/h), medium flow (10-40 km/h) and free flow (40 km/h and above) three states [14,15]. Guowen Dai etc. took factors such as space and time correlation of traffic flow into consideration, and proposed a prediction model for short-term traffic flow combining spatial and time analysis and Gated Recurrent Unit (GRU), which firstly conducted time & space correlation analysis on the collected traffic flow data, and then determined optimal interval of input time and spatial data volume by using the space-time feature-selection algorithm. At the same time, the selected traffic flow data was extracted from the actual traffic flow data and converted into a two-dimensional matrix with information of space-time traffic flow. The space-time characteristic information of the traffic flow inside the matrix was processed by GRU to achieve the purpose of prediction [16]. Zhe Dai et al. proposed a video-based vehicle counting framework, which applied YOLOV3 to detect the target, then created trajectory and tracks the target detected, and finally determined the driving direction taking advantage of the trajectory of the target, so as to obtain the traffic flow information [17]. C. Shiranthika et al. developed a high-precision real-time computer vision system that used background difference, morphological arithmetic and Gaussian filtering to track the vehicle's center of mass, thus accurately determining the vehicle's speed and count. The system also issued speed alerts when traffic jams reduced the permitted speed of the motorway [18].

To sum up, the current technology commonly used in the intelligent transportation system for the detection of abnormality on motorway traffic is video monitoring technology, which realizes recognition and tracking of motorway vehicle, analyzes state of traffic flow, whether there is retrogradation or collision through the video camera, so as to determine whether there are traffic anomalies. However, the video-detection method still has the following deficiencies:

A. The camera is greatly affected by the external environment

When the light is good, the camera has a good detection effect. Otherwise, the video captured by the camera may be blurred. Especially when there is occlusion and abnormal weather, the detection effect is greatly reduced, which even leads to the failure of detection.

B. Large amount of calculation for image processing

The video captured by the camera is composed of frame by frame. Then the data are collected and analyzed by using video detection technology and image processing technology to obtain traffic information. When a large quantity of traffic pictures are processed by computers, the computational pressure of computers increases, while the cost of high-

performance computers and hardware equipment for image processing enlarges.

C. Over-high pressure on transmission bandwidth of network

The growth speed of network bandwidth is far less than that of data. And the information collected by the equipment is directly transmitted to the server without any processing. Due to the continuity of information acquisition, the information transmission is also continuous, which will increase the pressure of network information transmission.

In view of the above problems, this paper proposes the analysis on motorway traffic anomalies based on time-space constraints, and puts forward the probability analysis method of traffic abnormalities on motorway based on time-space constraints, then establishes the probability estimation model of motorway traffic abnormalities at adjacent nodes. Firstly, the average arrival time of the traffic flow of adjacent nodes based on the morphological similarity distance is calculated, and Augment Dickey-Fuller is applied to judge whether the traffic-flow difference sequence of adjacent nodes is stable. For those with unstable difference sequence, the probability of traffic abnormality shall be calculated. If the probability value is greater than the set threshold, it shall be regarded as traffic abnormality.

II. BASED ON SPACE-TIME CONSTRAINTS EVALUATION OF HIGHWAY TRAFFIC ANOMALY PROBABILITY

Based on the statistical analysis of the traffic flow of adjacent nodes, a probability estimation model for traffic abnormalities at adjacent nodes of motorway based on space-time constraints is proposed. The assessment process is shown in Figure 1.

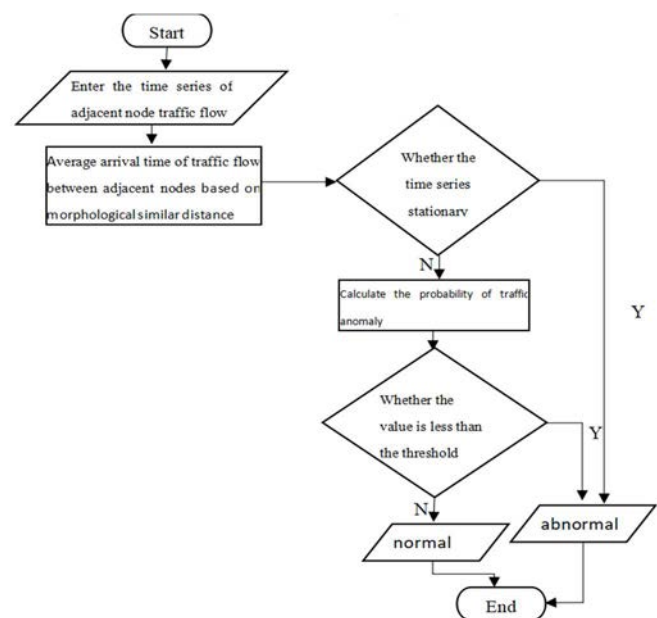


Figure 1. Flow chart of probability estimation for traffic abnormality at adjacent nodes of motorway based on space-time constraints

The marginal computing devices transmits counting results of motorway traffic flow to the cloud, and store them in the traffic-flow time series in the library, and then calculates average arrival time of traffic flow at adjacent nodes and tests whether the time series of traffic flow between two adjacent nodes apart from average arrival time are stable based on the morphological similarity distance. If the time series of traffic flow difference is not smooth, probability of traffic anomaly at adjacent nodes of motorway should be calculated. If the abnormal traffic probability is greater than the threshold, the abnormal traffic at adjacent nodes shall be considered, otherwise it will be deemed as normal transportation.

III. AN ALGORITHM FOR EVALUATING TRAFFIC ANOMALY PROBABILITY OF ADJACENT NODES BASED ON TIME AND SPACE CONSTRAINTS

Abnormal traffic on the motorway between adjacent nodes is reflected on the change of traffic flow intuitively, so the traffic flow through the adjacent nodes will significantly change. On the premise that the traffic flow at the i^{th} node of the marginal device remains unchanged, the traffic flow at the $(i+1)^{\text{th}}$ node of the marginal device will present decreasing trend for a period of time, the time series of traffic flow difference between adjacent nodes on the motorway presents a stationary time series. ADF^[19,20] stationarity test method is used to judge whether the time series of traffic flow difference between adjacent nodes of motorway is stable. When the time series of traffic difference between adjacent nodes of motorway is a stationary series, the traffic between adjacent nodes is normal. Otherwise, the traffic anomaly between adjacent nodes may occur. According to formula (2), the probability of traffic anomaly is represented by the percentage of the continuously decreasing sub-series in the time series of traffic difference between adjacent nodes on the motorway in the original time series.

$$P_{i+1,t} = \frac{NUM_{Z_t^-}}{NUM_{Z_t}} \quad (1)$$

$P_{i+1,t}$ presents the probability of traffic abnormality of the $i+1^{\text{th}}$ marginal device node on the motorway at the t time, $NUM_{Z_t^-}$ presents the number of elements in the continuously decreasing sub-sequence in the time series sequence of the $i+1^{\text{th}}$ and the i^{th} traffic-flow difference, NUM_{Z_t} presents the number of elements in the time series sequence of the $i+1^{\text{th}}$ and the i^{th} traffic-flow difference. A threshold value is set for traffic anomaly. When the probability of traffic anomaly is greater than a certain threshold value, traffic abnormality is identified between adjacent nodes of the motorway; Otherwise, the current traffic is considered normal.

IV. EXPERIMENT AND ANALYSIS

The experiment in this chapter mainly analyzes the time series of motorway traffic flow. Firstly, the average arrival time of motorway traffic flow is obtained by calculating the similar distance through the time series of motorway traffic flow at adjacent nodes. Then, the time series of traffic difference between adjacent nodes of motorway is obtained, and the probability of traffic anomaly is obtained through the

estimating stability of the time difference series of traffic flow. The experimental process is as follows:

A. Calculate the average arrival time of traffic flow

The sliding window selects a length of 20 and takes the traffic flow time series of adjacent nodes for a continuous 20 minutes. At time t , the traffic-flow time series of a node is 7,6,9,10, 9,8,9,11,6,7,7, 6,6,8,8,7,6,9,9. And the previous node of the traffic flow time series is 4,5,6,7,9,10,7,8,9,10,10,5,7,8,5,6,6,7,8,7,7,8,5,4,6,10,7,6,9,... . For each length moved by the sliding window, the similarity distance of traffic-flow time series at adjacent nodes is calculated, and the average arrival time of traffic flow is found through the minimum similarity distance. The experimental results of sliding window moving for 10 times are shown in Figure 2.

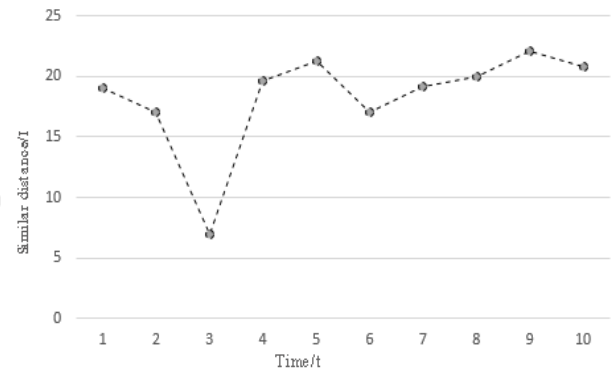


Figure 2. Variation of similar distance in traffic flow time series at adjacent nodes

It can be seen from Figure 2 that, with the movement of the sliding window, the similar distance of the time series of the motorway traffic flow at the adjacent nodes is changing constantly, but there will be an obvious downward and upward trend within a period of time, and there is a minimum value. When the similarity distance is the minimum, the traffic flow time series of adjacent nodes on the motorway is the most similar, and then the corresponding time is the average arrival time of the motorway traffic flow.

B. Time series of traffic flow difference on motorway

In experiment A, the average arrival time of traffic flows at adjacent nodes was obtained. Then, from the traffic-flow time series library of the motorway, the corresponding time series of traffic-flow difference between adjacent nodes of the motorway (as shown in Figure 3) was obtained, as shown in Figure 4.

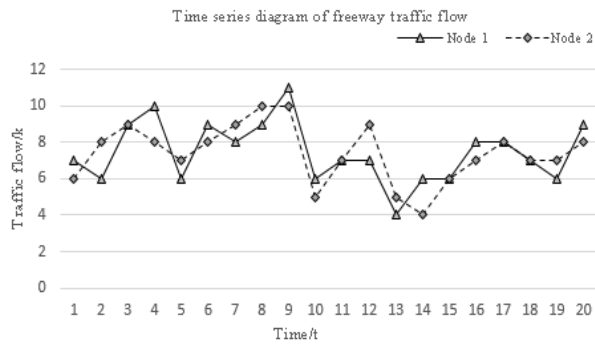


Figure 3. Time series diagram of motorway traffic flow at adjacent nodes

It can be concluded from Fig. 3 that the traffic flow time series of adjacent nodes present a similar trend. In the driving process of vehicle, due to different vehicle speeds, the motorway traffic-flow value of node 1 has a slight fluctuation based on the motorway traffic-flow value of node 2.

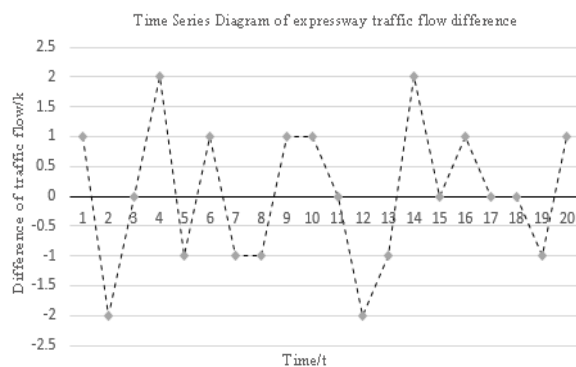


Figure 4. Time series diagram of traffic flow difference on the motorway

It can be seen from Fig. 4 that the value of traffic flow difference in the time series of traffic flow difference between adjacent nodes of the motorway fluctuates around 0 with a small fluctuation range.

C. Judgement of traffic abnormality on the motorway

In this paper, the motorway probability of traffic abnormality is judged by the time-series stationarity test of the traffic flow difference between adjacent nodes. The hypothesis of ADF stationarity test is that there is a unit root, namely, the motorway traffic flow time series is unstable. The time series of traffic flow difference between adjacent nodes when traffic is normal is shown in Figure 5, while that of traffic flow difference between adjacent nodes when traffic is abnormal is shown in Figure 6. The time series of traffic flow difference under the two conditions was tested for stationarity, and the results were shown in Fig. 7.

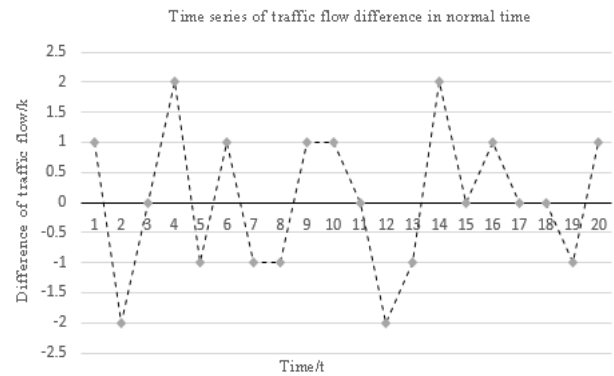


Figure 5. Time series diagram of traffic flow difference during normal traffic

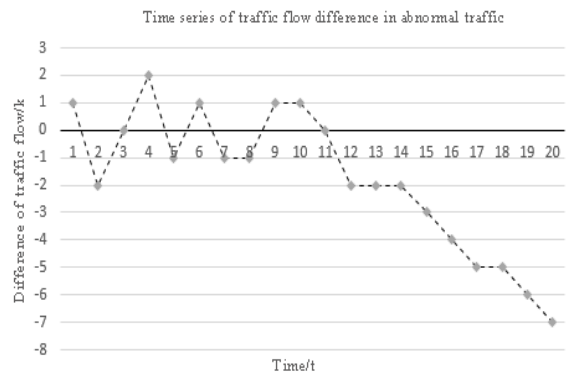


Figure 6. Time series diagram of traffic flow difference under abnormal traffic

normal: (-0.0,0.928532086060056,9,10,{ '1%':-4.331573,'10%':-2.7487,'5%':-3.23295},-632.7161896585883)
Abnormal:(0.029656695450461276,0.960917027983516,8,11,{ '1%':-4.223238279489106,'10%':-2.7729839421487603})

Figure 7. Test results for time-difference stationarity of traffic-flow difference

It can be seen from Fig 5 and Fig 7 that, under normal circumstances, the time series of traffic flow difference between adjacent nodes on the motorway fluctuates around the value of 0, which is relatively stable. Then, ADF test is used to test the stability of time series, the result of which can reject the original hypothesis that the time series is unstable.

It can be seen from Fig. 6 and Fig. 7 that in the case of traffic anomalies, the data graphic method shows that the time series of traffic flow difference on a section of motorway present a large trend change before and after a certain moment, and the declining trend becomes more and more obvious. The occurrence of traffic anomalies between adjacent nodes results in significant differences in traffic flow passing through adjacent nodes. The stability test of the time series is carried out and the original hypothesis is accepted. According to formula (1), the probability of traffic anomaly is calculated as 55%, which is greater than 50% of the threshold originally set.

V. CONCLUSIONS

In this paper, a probability estimation model for traffic anomalies at adjacent nodes of motorway is proposed based on space-time constraints. Firstly, according to the law of traffic flow changing with time in the time series library of motorway traffic-flow on the cloud server, the average arrival time of traffic flow of adjacent nodes is calculated according to the similar distance. Then, the time series of traffic flow difference between adjacent nodes is obtained, and the stationarity of the time series of traffic flow difference is tested by ADF stationarity test method, to calculate the probability of traffic anomaly between the adjacent nodes. When the calculated traffic anomaly probability value is less than or equal to a certain threshold value, it is considered that the current road is smooth and the traffic is normal. Otherwise, it is considered that the current road is abnormal, and abnormal information is sent to the marginal computing device. The experimental results prove the feasibility of the proposed method. Therefore, the probability assessment model of traffic anomalies at adjacent nodes of expressways based on space-time constraint can be used to evaluate traffic anomalies of expressways.

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Jun Guo, born in 1974, Ph.D., is a associate professor at Northeastern University. His research interests include edge computing, service computing and cloud computing.



Xinwei Liu, Studying a postgraduate in software engineering at Northeastern University, from 2019 to 2022, Shenyang, China, his research interests include edge computing, computer graphics and so on..



Chen Liu, born in 1990, master, is an experienter at Northeastern University. Her research interests include edge computing, smart hardware and wireless sensor network.



Zixuan Zhao, study as an undergraduate student in major of metallurgy from Northeastern University Shenyang China. He entered Northeastern University in September 2020. His research interests include Network Communications, edge computing and so on.



Bin Zhang, male, born in 1964, has a doctor's degree. He is the Dean, professor and doctoral supervisor of Software School of Northeast University. He is also the chairman of the steering committee of Computer Science in Liaoning Province.