

An automatic identification algorithm for freeway bottleneck based on loop detector data

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Abstract: A bottleneck automatic identification algorithm based on loop detector data is proposed. The proposed algorithm selects the critical flow rate as the trigger variable of the algorithm, which is calculated by the road conditions, the level of service and the proportion of trucks. The process of identification includes two parts. One is to identify the upstream of the bottleneck by comparing the distance between the current occupancy rate and the mean value of the occupancy rate and the variance of the occupancy rate. The other process is to identify the downstream of the bottleneck by calculating the difference of the upstream occupancy rate with that of the downstream. In addition, the algorithm evaluation standards, which are based on the time interval of the data, the detection rate and the false alarm rate, are discussed. The proposed algorithm is applied to detect the bottleneck locations in the Shanghai Inner Ring Viaduct Dabaishu-Guangzhong road section. The proposed method has a good performance in improving the accuracy and efficiency of bottleneck identification.

Key words: bottleneck; loop detector data; occupancy rate; flow rate

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Typical bottleneck analysis methods involve congestion graphics, vehicle arrival curves and the traffic flow theory. The methods above are based on the loop detector data. They assume that traffic patterns can be determined by the functional relationship of traffic flow and occupancy. The data analysis methods include decision trees, statistical analysis and filtering. With the development of data collection and information processing technology, the fuzzy theory, expert evaluation, pattern recognition, and artificial intelligence techniques have become important methods in congestion automatic identification algorithms. ACI algorithms can be divided into discrete and continuous types^[1-2]. The discrete method is based on the traffic parameter threshold. It is assumed that congestion occurs when a certain traffic parameter is

greater than the threshold value. In 1997, with the vehicle arrival curves, Cassidy et al.^[3] discussed the length of queues and waiting time in congestion. Based on the research findings of congestion, Bertini et al.^[4] proposed an automatic bottleneck recognition algorithm in 2005, identifying and classifying bottlenecks with historical data, and taking speed as the indicator of a bottleneck. However, these algorithms have not analyzed the statistical features of a bottleneck in detail, which decrease the precision of identification algorithms. Besides, most congestion identification algorithms were about congestion points. The research target of bottleneck identification is to discover the congestion influence scope, including the upstream and downstream of bottleneck locations. Therefore, a traffic flow analysis with more integrity is necessary.

In this research, based on loop detector data, the critical flow rate is calculated as the trigger variable, which is calculated by the road conditions, the level of service and the proportion of trucks. Occupancy is calculated as the identification parameters. In addition, algorithm evaluation standards are discussed.

1 Description of the Algorithm

A traffic bottleneck is a localized disruption of vehicular traffic on a street, road, or highway. As opposed to a traffic jam, a bottleneck is a result of a specific physical condition, often the design of the road, badly timed traffic lights, or sharp curves. They may also be caused by temporary situations, such as vehicular accidents. An algorithm based on occupancy differences between adjacent detectors to identify bottleneck locations and their activation and deactivation periods using loop detector data has been developed.

In this algorithm, the critical flow rate is defined as the trigger variable, and it is calculated based on the road conditions, the level of service and the proportion of trucks. When the flow rate is greater than the critical value, the identification process can start^[5-6].

1.1 Trigger variable of the algorithm

According to the traffic flow theory, when traffic demand exceeds road capacity, resulting in congestion, the flow rate decreases and congestion forms. Therefore, the flow rate can be used as the trigger variable of the algo-

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rithm. The critical flow rate is determined by the designed capacity and the level of service. User perceptions are variable at different time and in different environments. AASHTO design standards suggest that a good target level of service in an urban area is D, but in a rural area a good target level of service is C. Generally, when the level of service is C, average speeds begin to decline with increasing flow^[7]. We define the situation, in which the level of service is C, as the trigger point. However, it is difficult for the bottleneck automatic identification system to calculate the V/C ratio. The trigger value should be obtained immediately. Therefore, the accumulative flow rate in 5 min as the trigger variable is chosen. Tab. 1 lists the critical V/C ratio based on the level of service and the design speed. The capacity should be multiplied by the V/C ratio when the level of service is C to obtain the trigger value.

Tab. 1 Critical V/C ratio based on LOS and FFS

Design speed/ (km · h ⁻¹)	Level of service				
	A	B	C	D	E
100	0.40	0.69	0.91	1.00	> 1.00
80	0.34	0.61	0.83	1.00	> 1.00
60	0.30	0.55	0.77	1.00	> 1.00

The influence of large vehicle on traffic flow is not considered when calculating the free flow speed. Therefore, the trigger value obtained from Tab. 1 should be multiplied by f_{HV} .

1.2 Identification process

There are two elementary values which need to be defined in the bottleneck automatic identification algorithm. One is the minimum value of the difference between the upstream and downstream occupancy rates. The other one is the minimum value of the upstream occupancy rate. To define the difference between the upstream and downstream occupancy, it must be ensured that the upstream is in a state of congestion, and the downstream is free flow^[8-10].

Before defining the critical value, we should analyze the historical data to obtain the difference between the upstream and downstream occupancy rates. Experiments show that there are some overlaps in the difference between them. As this algorithm also requires the upper occupancy rate greater than a certain critical value, it should be ensured that the critical value of the difference between the upstream and downstream occupancy rates is smaller than the occupancy rate when a bottleneck occurs.

As the maximum upstream occupancy rate is affected by the road conditions, we use the distance between the current occupancy rate and the mean value of the occupancy rate from t_{s-1} to t_{s-6} instead of the maximum upstream occupancy rate. The distance between the current occupancy rate and the mean value of the occupancy rate

is equal to the current occupancy rate subtracting the mean value of occupancy rates from t_{s-1} to t_{s-6} .

$$D_{o_i} = O(i, t_s) - E(O_{t_{s-1}}, \dots, O_{t_{s-6}}) \quad (1)$$

where D_{o_i} is the distance between the current occupancy rate and the mean value of the occupancy rate from t_{s-1} to t_{s-6} ; $O(i, t_s)$ is the occupancy rate at t_s ; $E(O_{t_{s-1}}, \dots, O_{t_{s-6}})$ is the mean value of the occupancy rate from t_{s-1} to t_{s-6} .

If D_{o_i} is greater than the variance of the occupancy rate from t_{s-1} to t_{s-6} , we assume that unit i is the upstream of the bottleneck.

$$D_{o_i} = S(O_{t_{s-1}}, \dots, O_{t_{s-6}}) + \alpha \quad (2)$$

where $S(O_{t_{s-1}}, \dots, O_{t_{s-6}})$ is the variance of the occupancy rate from t_{s-1} to t_{s-6} ; α is the adjustment parameter.

Based on the definition of a bottleneck, the downstream of the bottleneck is free flow, which means that there is a value difference between the upstream and downstream occupancy. Experiments show that regional differences have an impact on the critical value of the difference between the upstream and downstream occupancy. Data analysis is a common method to determine the critical value of difference, but the analysis process is very complicated. In order to make the parameter in this algorithm universal, we use an adjustment parameter. To speed up the process of bottleneck identification, we also use the mean value of occupancy rate from t_{s-1} to t_{s-6} .

The difference between the upstream and downstream occupancy rates equals the current occupancy rate at point I , which subtracts the downstream occupancy rate. It should be noted that the value of n in the following formula requires several further tests.

$$P(t_s) = O(i, t_s) - O(i + n, t_s) \quad (3)$$

where $P(t_s)$ is the difference between the upstream occupancy rate and that of the downstream; $O(i, t_s)$ is the downstream occupancy rate at point i ; $O(i + n, t_s)$ is the occupancy rate, $n = 1, 2, \dots$

The critical value of difference after adjustment equals the difference between the upstream occupancy and the downstream occupancy, divided by the mean value of the occupancy rate from t_{s-1} to t_{s-6} .

$$P_r(t_s) = P(t_s) / E(o_{t_{s-1}}, \dots, o_{t_{s-6}}) \quad (4)$$

where $P_r(t_s)$ is the critical value of difference after adjustment; $E(o_{t_{s-1}}, \dots, o_{t_{s-6}})$ represents the mean value of the occupancy rate from t_{s-1} to t_{s-6} .

The parameter i in Eq. (3) is defined as the section of pavement units when identifying the location of the bottleneck. The value of i equals the longitudinal space of loop detectors, which is 20 or 50 m on the expressway.

The parameter t is defined as the data aggregation lev-

el. The original loop detector data is collected every 20 s, which is highly volatile. Different data aggregation levels can affect the promptness and accuracy of the algorithm. So the original loop detector data should be facilitated aggregation before being used in the algorithm. Details will be discussed in the following section.

Fig. 1 shows the process of bottleneck automatic identification.

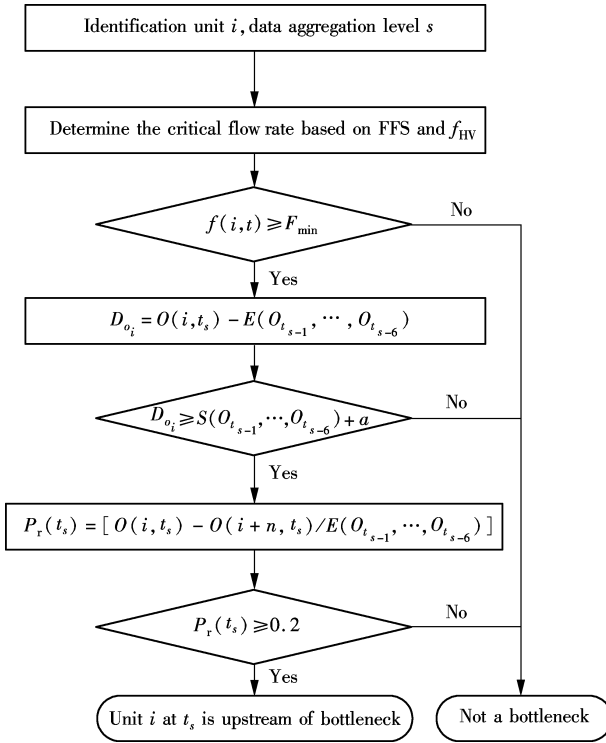


Fig. 1 The process of bottleneck automatic identification

As shown in Fig. 1, the first step of the bottleneck identification algorithm is to divide the road section into several units and to determine data aggregation level. Then, the critical rate of flow is calculated. After preprocessing, $f(i, t)$ is compared with the critical rate. If $f(i, t)$ is greater, the process of bottleneck identification can start. The process of identification includes two parts. One is to identify the upstream of the bottleneck by comparing the distance between the current occupancy rate and the mean value of occupancy rate D_{o_i} with the variance of the occupancy rate. If D_{o_i} is greater than the variance of the occupancy rate from t_{s-1} to t_{s-6} , assume that unit i is the upstream of bottleneck. The other is to identify the downstream of bottleneck by calculating $P_r(t_s)$. If $P_r(t_s)$ is greater than 0.2, assume that unit $i + n$ is the downstream of bottleneck.

1.3 Evaluation model

The accuracy of this automatic recognition algorithm of the bottleneck should be determined by three aspects. The first aspect is the percentage of the bottleneck points that can be recognized at all the bottleneck points; the second

is the percentage of “fake bottleneck points” in the bottleneck points that are recognized; and the third is the time interval of the date which can also influence the sensitivity of the algorithm. In practice, regional differences make it difficult to balance the failure of recognizing the real bottleneck points and the mistaken recognition of “fake bottleneck points”. So the optimal choice of parameters depends on the user’s choice of a composite score function that takes the relative costs of missed bottlenecks and false alarms into account.

The percentage of the bottleneck points recognized equals the number of the bottleneck points which have been recognized divided by the number of the total bottleneck points. While the percentage of “fake bottleneck points” equals the number of the fake bottleneck points which have been recognized, divided by the number of the total bottleneck points which have also been recognized.

$$T = \frac{t_b}{n_b} \quad (5)$$

where T is the percentage of the bottleneck points recognized; t_b is the number of the bottleneck points which have been recognized; n_b represents the number of the whole bottleneck points.

$$F = \frac{f_b}{i_b} \quad (6)$$

where F means the percentage of “fake bottleneck points”; f_b is the number of the fake bottleneck points which have been mistaken; i_b is the number of the total bottleneck points which have been recognized.

The accuracy of this automatic recognition algorithm of bottleneck can be calculated as

$$S = \beta(\alpha_T T - \alpha_F F) \quad (7)$$

where S is the accuracy of this automatic recognition algorithm of the bottleneck; β is the correction coefficient determined by the time interval; α_T is the penalty weight of the success rate; α_F is the penalty weight of the false-alarm rate.

2 Actual Analysis

One-week (from Sept 21 to Sept 27, 2012) loop detector data on the Shanghai Inner Ring Viaduct (5:00—11:00, 14:00—20:00) were obtained from the Shanghai Transportation Operation Department. The research scope starts from Dabaishu and runs to Guangzhong Road.

The first step of the bottleneck identification algorithm is to divide the road sections into several units and determine the data aggregation level. In this research, the number of road units is determined by the spacing of loop detectors. If the loop detector data is aggregated into 1-min data, the algorithm should be restricted by some ad-

ditional conditions. For example, a sustained bottleneck filter is added to smooth the results of the algorithm. This filter discards false positives that are isolated in the time dimension from other detections at the same location.

It can be seen from Fig. 1 that when loop detector data is aggregated into 3-min data sets, the upstream occupancy remains greater than the downstream occupancy but the difference in values fluctuates greatly. To obtain higher recognition rate, the difference between the upstream and downstream occupancy should be set to be small, which will increase the possibility of false alarm bottlenecks. Then we facilitate further aggregation into 5-min and 10-min data sets. As Figs. 2(b) and (c) show, the occupancy rates in bottlenecks (O_i) remain stable.

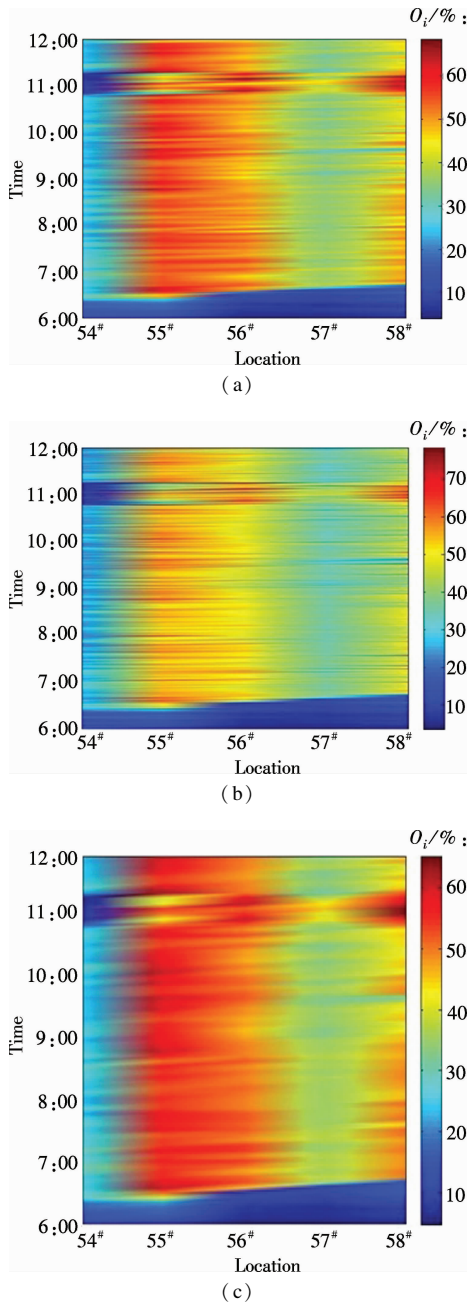


Fig. 2 Baseline analysis of bottleneck locations. (a) 3-min data; (b) 5-min data; (c) 10-min data

Based on the above analysis, we conclude that the smaller time interval leads to higher sensitivity. Experiments show that 5-min aggregation data fits the algorithm best.

In Tab. 1, critical V/C ratio is 0.83 when the level of service is C and the design speed is 80 km/h. Then, f_{HV} is 0.9. The design capacity of the Shanghai Inner Ring Viaduct is 1 800 (pcu · h⁻¹)/lane. Thus, the final critical flow rate in 5 min is 108 pcu.

Then we input the 5-min data sets to Matlab. When the flow rate is greater than 108 pcu, the algorithm starts. If D_{oi} is greater than the variance of the occupancy rate from t_{s-1} to t_{s-6} , assume that unit i is the upstream of the bottleneck. If $P_r(t_s)$ is greater than 0.2, assume that unit $i + n$ is the downstream of the bottleneck.

The session is identified by Matlab in a space-time distribution airstrip, as shown in Fig. 3.

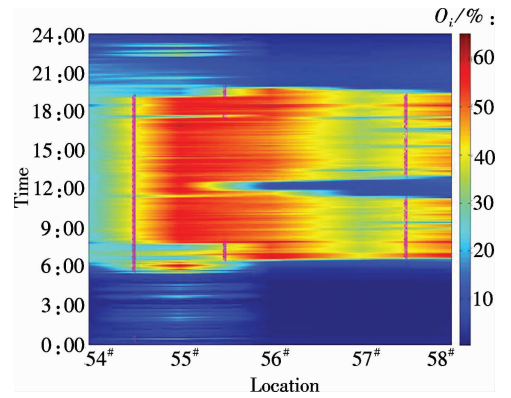


Fig. 3 Bottleneck identified with the algorithm

Fig. 3 presents the bottleneck locations identified which are marked with the triangles. In this analysis, three severe bottleneck locations were found.

The point where No. 56 loop detector is located becomes congested at 6:55, giving rise to congestion and vehicle delays between the No. 55 loop detector and No. 56 loop detector. The occupancy rate starts to decrease at 9:20, which means that the congestion has started to be relieved. The road section between the No. 56 loop detector and No. 58 loop detector is free flow between 6:00 and 6:35. Then the occupancy rate begins to increase and the point where the No. 58 loop detector is located becomes congested at 7:10. The occupancy rate begins to decrease at 8:40. Finally, the road section has free flow at 9:45.

3 Evaluation

In section 2, we analyze the distribution of the bottleneck in time and space through identifying bottleneck locations and their activation and deactivation periods. On the other hand, we are informed of the real distribution of bottlenecks through video data. Based on this, the accuracy of the proposed algorithm is confirmed. The evaluation consists of a series of indices, including the detection rate T and the false alarm rate F .

It can be seen from Tab. 2 that the proposed algorithm has a reasonable detection performance compared to other methods. Otherwise, the percentage of fake bottleneck points is 0. 1. The critical flow rate and the occupancy threshold value are decreased to increase T . The parameter values can be optimized to decrease F in application.

Tab. 2 Evaluation results of the proposed algorithm

Evaluation parameter	Value
T	0. 95
F	0. 10
S	0. 85

The proposed algorithm also outperforms previous cumulative curve methods in terms of precision and identification efficiency. In the cumulative curve method, each identification process is subject to interference by earlier data. In the proposed algorithm, the identifying process is only determined by the current data.

4 Conclusion

- 1) The statistical analysis of loop detector data shows that the flow rate and occupancy are more reliable parameters than speed for bottleneck identification, excluding affection by speed limits.
- 2) Loop detector data should be aggregated before the identification process. Experiments show that a 5-min aggregation data fits the algorithm best.
- 3) A bottleneck identification algorithm based on the flow rate and occupancy is proposed. The proposed algorithm includes the trigger variable, the identification process and the evaluation model. The algorithm reduces the influence of road conditions and data error by parameter optimization. The results show that the proposed algorithm has a good performance in improving the accuracy of bottleneck identification.
- 4) Although the results are encouraging, a number of extensions to the algorithm need to be studied. Further research should be carried out to validate this algorithm on

other types of roads. Note also that the original loop detectors data should be aggregated before analysis and that we need toseek a better method of data aggregation to increase the speed of the algorithm.

References

[1] Chung K, Rudjanakanoknad J, Cassidy M J. Relation between traffic density and capacity drop at three freeway bottlenecks[J]. *Transportation Research Part B: Methodological*, 2007, **41**(1): 82 – 95.

[2] Banks J H. Review of empirical research on congested freeway flow [J]. *Transportation Research Record*, 2002, **1802**: 225 – 232.

[3] Cassidy M J, Windover J R. Methodology for assessing dynamics of freeway traffic flow[J]. *Transportation Research Record*, 1995(1484): 73 – 79.

[4] Bertini R L, Myton A. Using PeMS data to empirically diagnose freeway bottleneck locations in Orange County, California [J]. *Transportation Research Record*, 1925, **2005**: 48 – 57.

[5] Shoraka M, Puan O C. Review of evaluating existing capacity of weaving segments[J]. *International Journal of Civil and Structural Engineering*, 2010, **1**(3): 683 – 694.

[6] Coifman B, Mishalani R, Wang C, et al. Impact of lane-change maneuvers on congested freeway segment delays; pilot study [J]. *Transportation Research Record*, 2006, **1965**: 152 – 159.

[7] Cassidy M J, Mauch M. An observed traffic pattern in long freeway queues [J]. *Transportation Research Part A: Policy and Practice*, 2001, **35**(2): 143 – 156.

[8] Kumar R, Wolenetz M, Agarwalla B, et al. DFuse: a framework for distributed data fusion[C]//*Proceedings of the 1st International Conference on Embedded Networked Sensor Systems*. Los Angeles, CA, USA, 2003:114 – 125.

[9] Newell G F. A simplified car-following theory: a lower order model[J]. *Transportation Research Part B: Methodological*, 2002, **36**(3): 195 – 205.

[10] Cassidy M J. Bivariate relations in nearly stationary highway traffic[J]. *Transportation Research Part B: Methodological*, 1998, **32**(1): 49 – 59.

基于线圈数据的瓶颈点自动识别算法

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摘要:提出了一种基于线圈数据的瓶颈点自动识别算法. 算法以临界流量作为算法的触发变量,根据道路条件、服务水平和大型车比例计算临界流量. 算法的识别程序包括2部分:首先通过计算当前占有率与前时刻占有率的相对差值来判定瓶颈点上游位置;然后通过计算上游占有率与下游占有率的相对差值确定瓶颈点下游的位置. 此外,提出了基于数据集计周期、瓶颈点识别率和误判率的算法性能评价方法. 利用上海市内环高架大柏树一广中路段的线圈数据进行试验,结果表明,瓶颈点自动识别算法在准确率和效率上有显著提高.

关键词:瓶颈点;线圈数据;占有率;流量

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