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Online Identification of Low-Speed Misfit Driving Behavior based on Fuzzy Comprehensive Evaluation Method and XGBoost Algorithm

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Abstract: Timely identification of low-speed misfit driving behavior is essential for enhancing road traffic safety and operational efficiency. This paper proposes an online recognition method for detecting such behavior. First, eight characteristic indicators are selected and quantified from the perspectives of the vehicle itself and the vehicles ahead and behind. Then, thresholds are determined using the interquartile range method, and indicator weights are calculated using the CRITIC method. A membership function is constructed to perform a fuzzy comprehensive evaluation and determine the behavioral state of the vehicle. Finally, the XGBoost algorithm is applied to train an online recognition model using the feature indicators and evaluation results, with the model validated on the highD dataset. The results demonstrate that the fuzzy comprehensive evaluation method, based on the eight defined indicators, effectively identifies low-speed misfit vehicles. The XGBoost model further enhances recognition accuracy. This research provides valuable insights for transportation authorities in managing vehicle behavior and maintaining efficient and stable traffic flow. It also holds practical significance for alleviating congestion and ensuring unimpeded access for critical services such as ambulances and disaster response vehicles.

Keywords: Traffic Engineering; Driving Behavior Identification; Fuzzy Comprehensive Evaluation; Low-Speed Outlier Driving Behavior; Moving Bottleneck.

1. Introduction

Under ideal traffic conditions, all vehicles on the road would travel at their desired maximum speeds in a stable, uniform, and efficient manner—effectively forming a "platoon." However, in practice, differences in driver behavior and vehicle performance result in varying travel speeds across vehicles, leading to mutual interference and increased complexity in traffic dynamics [1]. Some drivers, despite having adequate space to accelerate and sufficient vehicle capability, maintain significantly lower speeds than surrounding traffic. This obstructs following vehicles and causes frequent acceleration, deceleration, and lane changes, ultimately increasing speed variance on the road and negatively impacting traffic safety [2]. These effects can propagate upstream, often forming moving bottlenecks that contribute to traffic congestion [3].

Researchers have long recognized the impact of low-speed vehicles and have conducted extensive studies on this topic. In 1992, Gazis et al. [4] identified that some heavy trucks could trigger a chain reaction of deceleration among surrounding vehicles, leading to the formation of slow-moving convoys, coining the term "moving bottleneck." Subsequent studies explored the formation and evolution of such bottlenecks through modeling and simulation. For instance, Newell [5] represented moving bottlenecks as fixed bottlenecks by introducing a moving coordinate system, while Lebacque [6] proposed the KW-MB model, which was later extended to consider interactions among multiple moving bottlenecks. Jia Bin [7] incorporated a honking mechanism into simulation models and found that honking could prompt slower vehicles to yield, accelerating the dissipation of bottlenecks. Lin Hangfei et al. [8] analyzed spatial and temporal characteristics of moving bottlenecks across domestic and international highways, and suggested countermeasures such as periodically widening road sections to facilitate overtaking—an approach shown to enhance freeway flow.

To date, most studies have focused on vehicle speed as the primary indicator of low-speed behavior and have emphasized mitigation strategies after bottlenecks form. However, fewer studies address how to identify and prevent such behaviors at an early stage. Moreover, the definition of "low-speed" remains ambiguous, with varying criteria used across different studies. In urban expressways without a minimum speed limit, or when surrounding traffic is sparse, vehicle speed alone may have limited influence on overall traffic flow. Therefore, this paper proposes a new concept—low-speed misfit driving behavior, which refers to drivers who persistently maintain relatively low speeds and disrupt surrounding traffic flow, even in the absence of external constraints.

Timely and accurate identification of such behavior is crucial for traffic authorities to issue early warnings and implement interventions, such as acceleration prompts or lane change suggestions. These actions are key to reducing the formation of moving bottlenecks and improving roadway efficiency.

With the advancement of communication technologies and telematics, traffic authorities now have access to high-resolution, multidimensional trajectory data that includes speed, acceleration, and other driving parameters. This micro-level data is widely used in driving behavior studies and plays an important role in improving traffic safety [9]. For instance, Toledo et al. [10] collected in-vehicle data to assess driver risk based on lane changes, speeding, and rapid deceleration. Castignani et al. [11] employed fuzzy logic to evaluate risky behavior using metrics such as excessive speed and abrupt acceleration or deceleration. Cheng Guozhu et al. [12] used simulation experiments to identify dangerous driving under icy and snowy conditions based on indicators like steering jerks and sudden speed changes. Wu Jianqing et al. [13] designed naturalistic driving experiments and developed nine indicators for identifying hazardous truck driving. Xue Qingwen et al. [14][15] used the Minimum Time to Collision (MMTC) risk parameter and trajectory features to evaluate and recognize dangerous behavior via the LGBM model.

Most of these studies rely primarily on indicators derived from the vehicle itself. However, since drivers must continuously monitor and react to surrounding traffic, incorporating relative behavior metrics, such as interactions with vehicles ahead and behind, can yield a more accurate and comprehensive understanding of driving behavior.

Building on this foundation, the present study introduces the concept of low-speed misfit driving behavior by incorporating both self-driving data and relative behavior with adjacent vehicles. A fuzzy comprehensive evaluation method is employed to determine whether a vehicle is exhibiting misfit behavior. Subsequently, an XGBoost-based online recognition model is developed, which inputs the extracted feature indicators and evaluation results to identify misfit behavior in real time. The model's performance is validated using the highD dataset, confirming its effectiveness in detecting and characterizing low-speed misfit drivers.

1.1. Model Construction for Online Identification of Low-Speed Misfit Driving Behavior

In this paper, we define the driving behavior that is relatively low-speed and affects the surrounding vehicles as low-speed misfit driving behavior, and its impact on the traffic flow is shown in Figures 1 and 2. Where C is the target vehicle, C_F is the vehicle in front of the vehicle, C_B is the vehicle behind the vehicle, and d_F is the distance between the vehicle and the vehicle in front of it.

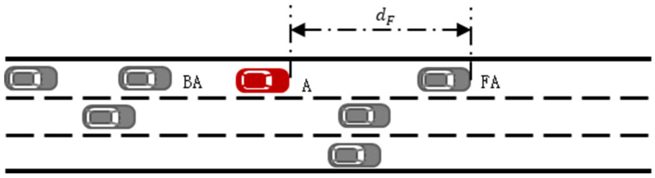


Fig 1. Initial appearance of low-speed misfit vehicles

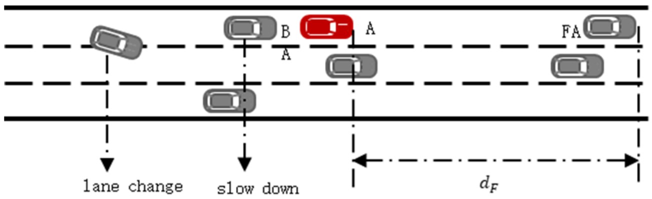


Fig 2. Low-speed misfit vehicles appear for a while

It can be seen from Figs. 1~2 that vehicles generating low-speed misfit driving behavior show a tendency to move away from the front vehicle and force the rear vehicle to reduce its speed. Accordingly, this paper proposes a method for determining low-speed out-of-group driving behavior that takes into account the individual operating characteristics of the vehicle and the driving fluctuations relative to the front and rear vehicles, extracts a total of eight feature indicators, constructs the affiliation function, and establishes a fuzzy comprehensive evaluation model to determine whether the vehicle is in the state of low-speed out-of-group driving behavior. After that, the XGBoost algorithm is combined with the input of feature indicators and judgment results for training to realize the online recognition of low-speed out-of-group driving behavior.

1.1.1. Characterization Indicator Assignment

Indicators of specific characteristics of low-speed uncongenial driving behavior are shown in the table below:

Table 1. Characteristic indicators

Type of characterization indicator	Name of characteristic indicator	unit (of measure)
Individual driving characteristics	tempou_1	m-s-1
	accelerationu_2	m-s-2
Characterization of driving fluctuations relative to the vehicle in front	Difference in speed from the vehicle in front u_3	m-s-1
	Difference in acceleration from the vehicle in front u_4	m-s-2
	Difference in distance from the vehicle in front u_5	m
Characterization of driving fluctuations relative to the rear vehicle	Difference in speed from the rear u_6	m-s-1
	Acceleration difference with the rear vehicle u_7	m-s-2
	Difference in distance from the rear u_8	m

1.2. Characterization Index Threshold Determination and Weight Calculation

After the calculation of the value of each characteristic index of low-speed misfit driving behavior is completed, the threshold value and weight of each index need to be determined in order to subsequently determine the segmentation point of the affiliation function through the threshold value, and calculate the total affiliation through the weight.

1.2.1. Threshold Determination

In this paper, we use the quartile difference method to determine the threshold value, which applies to all kinds of outlier judgment. The calculation formula is as follows:

$$M_i = Q_i \pm 1.5 I_i \tag{1}$$

Where: M_i is the threshold value of the low-speed misfit driving behavior indicator of the first i; Q_i is the upper quartile, the symbol is taken as "$+$ "; Q_i is the lower quartile, the symbol is taken as "$-$ "; I_i is the difference between the upper and lower quartiles.

1.2.2. Calculation of Weights

In this paper, the objective assignment method is chosen to determine the weights of each feature indicator, whose advantage lies in the comprehensive measurement of each indicator through the comparative intensity and conflictiveness, without relying on the subjective judgment of experts[14]. The calculation formula is as follows:

$$w_i = \frac{c_i}{\sum_{j=1}^{n} c_j} \tag{2}$$

$$c_i = \delta_i R_i = \delta_i \sum_{j=1}^{n} (1 - r_{ij}) \tag{3}$$

Where: w_i is the weight of the first i feature indicator; c_i is the information content of the first i feature indicator; δ_i is the standard deviation of the first i feature indicator, i.e., the contrast strength of the feature indicator; r_{ij} is the relationship coefficient between the feature indicator i and the feature indicator j.

1.3. Fuzzy Integrated Evaluation Model

The above derives the values of each characteristic index of low-speed misfit driving behavior and their thresholds and weights, on the basis of which, the fuzzy comprehensive evaluation method[16][17] is used to make judgments on low-speed misfit driving behavior. The specific steps are as follows:

(1) Determine the set of evaluation factors. The set of factors is a collection of factors affecting the object evaluation, $U = \{u_1, u_2, u_3, \cdots, u_i, \cdots u_n\}$, where the evaluation factors are the eight indicators mentioned above.

(2) Determine the evaluation set. Evaluation set is a collection of various possible results of the evaluation object,$V = \{v_1, v_2, v_3, \cdots, v_j, \cdots v_m\}$, Here, the evaluation set is divided into low-speed non-conformity type, normal type, and over-speed type.

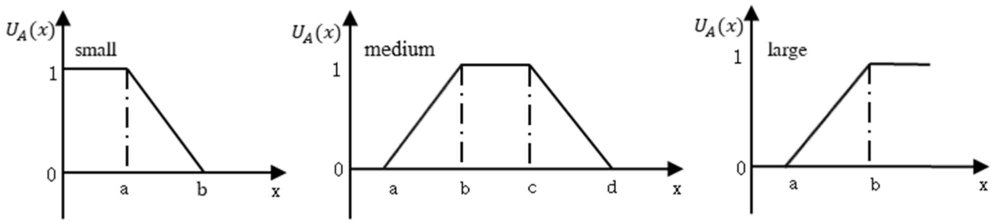
(3) Determine the fuzzy comprehensive judgment matrix. The fuzzy comprehensive judgment matrix is as follows:

$$R_{nm} = \begin{bmatrix} R_1 \\ \vdots \\ R_n \end{bmatrix} = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} \tag{4}$$

whereR_{ij} is the affiliation of the i The vehicle concerning the j evaluation set.

(4) Judgment. According to the size of the affiliation degree of each evaluation set, judge whether the sample belongs to which category of evaluation set. Here that is, to judge the vehicle belongs to the low-speed misfit, normal, speeding which one.

The affiliation function satisfies 0<= $u(x)$ <= 1, i.e., for each element x, there is a corresponding value. In practical applications, trapezoidal affiliation function and triangular affiliation function are often used, and then analyzed in combination with the practical application scenarios to determine which one of the functions belongs to the partial large, partial small, and intermediate type, and take the value of[18] for each segmentation point. In this paper, we choose to construct the trapezoidal affiliation function, and the function and image are shown below:



$$U_A(x) = \begin{cases} 1, & x \le a \\ \dfrac{b-x}{b-a}, & a < x < b \\ 0, & x \ge b \end{cases}$$

$$U_A(x) = \begin{cases} 0, & x \le a, x \ge d \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c < x < d \end{cases}$$

$$U_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & x \ge b \end{cases}$$

Fig 3. Small, medium, and large

1.4. XGBoost Online Recognition Models

Based on the eigenvalues and determination results above, the combination with machine learning algorithms is considered to build an online recognition model for low-speed misfit driving behavior. Extreme Gradient Boosting Tree (XGBoost) has significant advantages in training speed, prediction accuracy, and model performance, and is widely used in driving behavior recognition[19] . Based on this, this paper chooses to apply the XGBoost algorithm to build an online recognition model for low-speed misfit driving behavior.

2. Data Processing

2.1. Data Sources

In this paper, the German highD dataset[20] is selected for analysis, and the observation data from measurement point 1 is chosen. The measurement point is located on the A3 highway in the western part of Cologne, with 6 lanes. The length of the data collection area is 420 m, and the speed limit is 33.33 m-s^{-1}, the interval belongs to the road section without intersections, entrances and exits, and so on.

Table 2. Data Collection Schedule

data segment	Starting time	Duration (s)	data segment	Starting time	Duration (s)
25	8:55	1178.4	30	11:03	1202.04
26	9:20	1120.56	31	11:28	1118.04
27	9:46	1208.84	32	12:20	777.32
28	10:12	1250.96	33	12:41	1111.48
29	10:39	1119.4	34	13:34	844.16

Ten data segments were recorded, starting at 8:55 and lasting between 10 and 20 minutes each, with the final segment ending at 13:34. In total, 25,340 trolley data points were collected, as summarized in Table 2. Each segment was visualized and examined, and the data from segments 28 to 34, corresponding to free-flow traffic conditions, were selected for subsequent analysis.

2.2. Sample Extraction

Driving data from the lane was selected for analysis. The speed vvv, acceleration aaa, and position xxx of vehicle A, along with those of its preceding vehicle FAF_AFA and following vehicle BAB_ABA, were extracted to calculate the eight-feature metrics outlined above. The corresponding calculation formulas are summarized in the table below:

Table 3. Calculation of characteristic indicators

Characteristic indicators	formulas	unit (of measure)	Characteristic indicators	formulas	unit (of measure)
u_1	v_A	m-s-1	u_5	$x_{FA} - x_A$	m
u_2	a_A	m-s-2	u_6	$v_{BA} - v_A$	m-s-1
u_3	$v_{FA} - v_A$	m-s-1	u_7	$a_{BA} - a_A$	m-s-2
u_4	$a_{FA} - a_A$	m-s-2	u_8	$x_A - x_{BA}$	m

To ensure accuracy, the samples were screened to exclude instances involving lane-changing behavior and those with durations shorter than 10 seconds. Each sample was uniquely identified using a combination of the data segment name and vehicle ID. After filtering, a total of 1,533 vehicle samples were retained for subsequent analysis.

3. Model Validation

3.1. Determining Thresholds, Weights, and Constructing Affinity Functions

Thresholds and weights of the characteristic indicators were calculated using the quartile difference method and CRITIC above, respectively, and three types of affiliation functions were constructed for low-speed nonconformity, normal, and overspeed. The segmentation points of the partial-small function are the lower threshold and 5% quantile, the segmentation points of the intermediate function are the 5% quantile, 25% quantile, 75% quantile and 95% quantile, and the segmentation points of the partial-large function are the 95% quantile and the upper threshold[22]. The values of the segmentation points of the affiliation function are shown in the table below:

Table 4. The value of the segment point

Characteristic indicators	Low-speed misfits	normal type	overspeed
u_1	on the small side a: 22.8 b: 24.62	intermediate a: 24.62 b: 28.28 c: 31.93 d: 33.77	oversize a: 33.77 b: 37.41
u_2	on the small side a: -0.89 b: -0.76	intermediate a: -0.76 b: -0.22 c: 0.23 d: 0.63	oversize a: 0.53 b: 0.91
u_3	oversize a: 2.27 b: 3.22	intermediate a: -2.27 b: -0.61 c: 0.92 d: 2.27	on the small side a: -2.9 b: -2.27
u_4	oversize a: 0.74 b: 0.95	intermediate a: -0.59 b: -0.18 c: 0.27 d: 0.74	on the small side a: -0.86 b: -0.59
u_5	oversize a: 62.16 b: 66.8	intermediate a: 17.15 b: 24.57 c: 41.46 d: 62.16	on the small side a: 0 b: 17.15
u_6	oversize a: 2.64 b: 3.28	intermediate a: -2.18 b: -0.82 c: 0.82 d: 2.64	on the small side a: -3.28: -2.18
u_7	oversize a: 0.66 b: 0.95	intermediate a: -0.76 b: -0.28 c: 0.21 d: 0.66	on the small side a: -1.02 b: -0.76
u_8	on the small side a: 0 b: 17.07	intermediate a: 17.07 b: 24.17 c: 40.59 d: 60.97	oversize a: 60.97: 65.22

3.2. Determination of Results

The index values of low-speed misfit driving behavior characteristics of all the samples were brought into the corresponding affiliation function and multiplied by the corresponding weights to get the total affiliation of each sample. By comparing the affiliation degree of each type of evaluation results, the following judgment results are obtained:

Table 5. Judgment Results

Sample of low-speed misfits	Normal type sample	Over-speed type sample
23	1502	8

Since the objective of this study is low-speed misfit driving behavior, the latter section focuses on the analysis of the identified 23 low-speed samples. The mean and standard deviation of speed and acceleration are analyzed by comparing the difference in driving behavior between low-speed misfit vehicles and normal vehicles. With a sliding window of 10s, 71 low-speed misfit driving behavior segments were obtained, while 100 normal driving behavior segments were randomly selected, and the results are shown in Figs. 5 and 6: low-speed misfit driving behaviors present smaller means and larger standards in terms of speed and acceleration compared to normal driving behaviors. This suggests that drivers' occurrence of low-speed misfit driving behavior is accompanied by more deceleration operations, which is consistent with the pattern in the actual traffic flow.

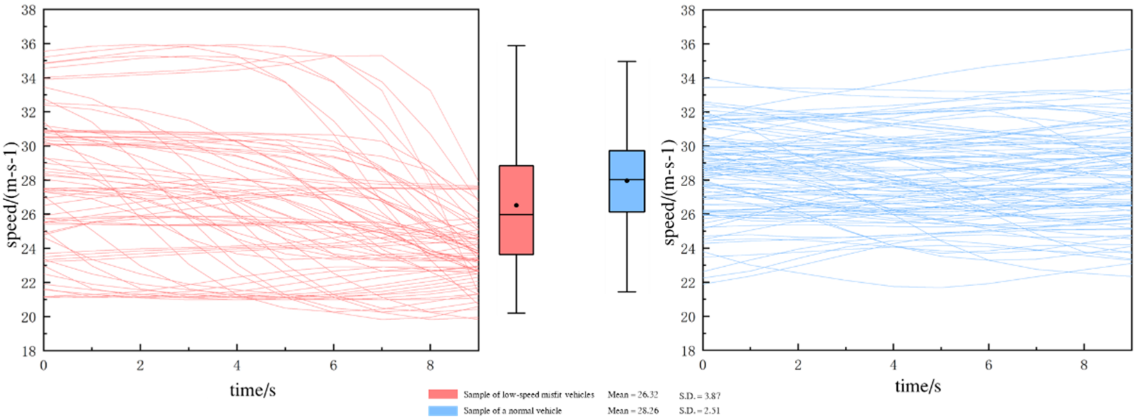


Fig 4. Statistical description of speed

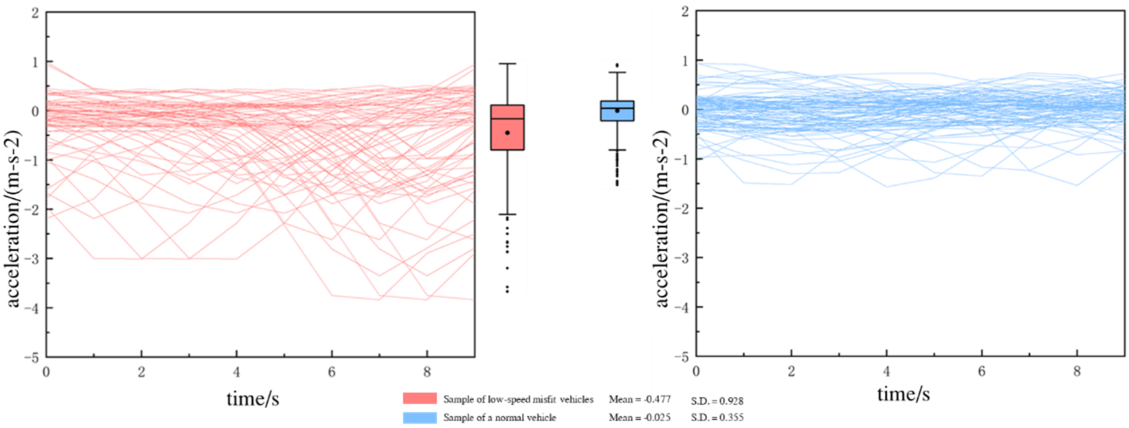


Fig 5. Statistical description of acceleration

Combined with the analysis of vehicle trajectory data, it can be found that: the results contain two forms of low-speed out-of-group driving behavior, the first is initially driving at a normal speed, and then continue to slow down; the second is the initial speed is lower, and then continue to maintain a low speed or slow down. The screened low-speed misfit vehicles Table 43-1738 and Table 34-722 are listed below, respectively, and compared and analyzed with the normal driving vehicles Table 29-1929, as shown below:

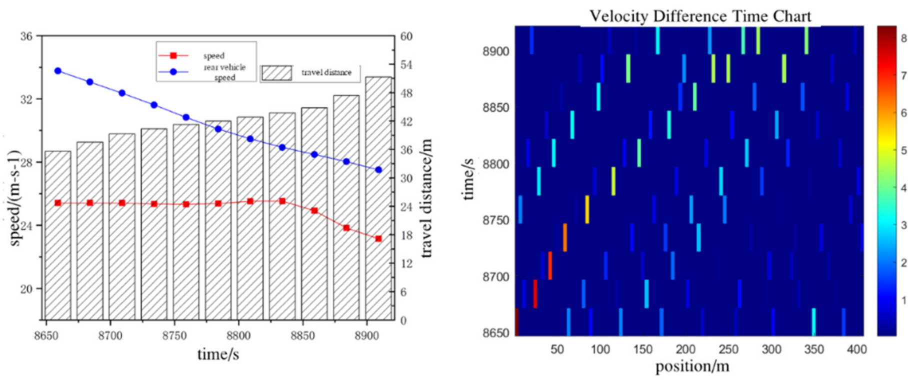


Fig 6. Table 43-1738 (low-speed misfit sample)

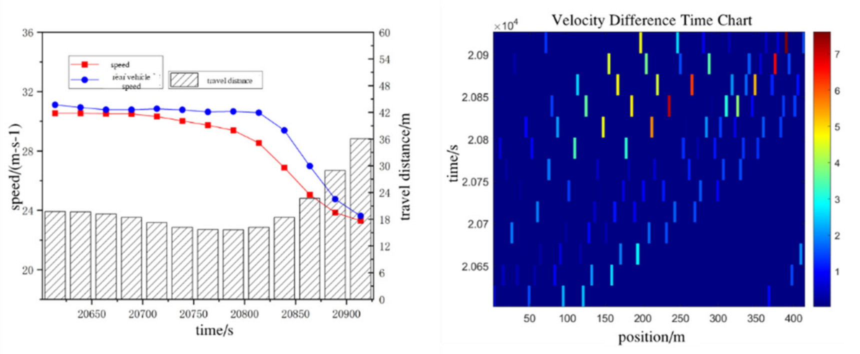


Fig 7. Table 34-722 (low-speed misfit sample)

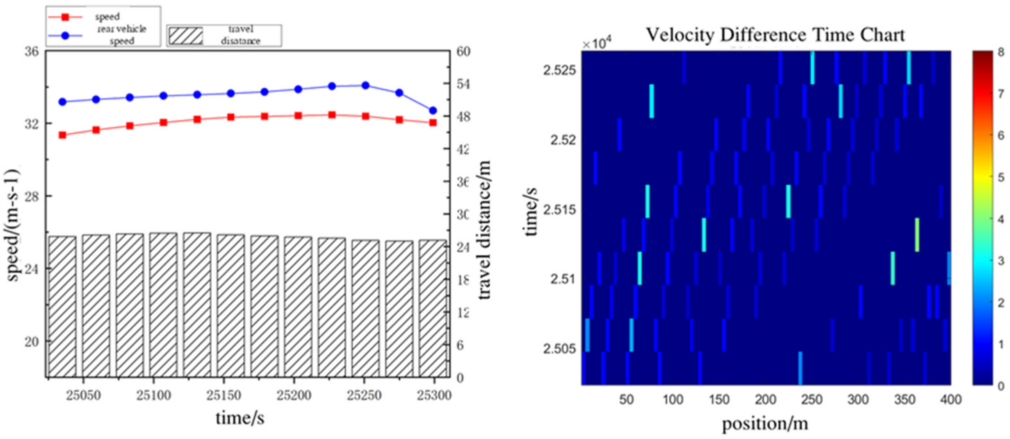


Fig 8. Table 29-1929 Cars (Other Samples)

In Figures 6, 7, and 8, the left graph shows the changes in vehicle speed, rear vehicle speed, and distance from the vehicle in front, and the right graph shows the absolute value of the speed difference between vehicles on the road during the period from the appearance of the vehicle to its departure. It can be seen that: the normal vehicle in the left graph and the rear vehicle driving in a relatively stable state, speed fluctuation is not big; produce low-speed uncongenial driving behavior of the vehicle on the rear vehicle to influence, forcing the rear vehicle also slow down to follow the speed, and the vehicles are showing a tendency to move away from the vehicle in front of them. In the right figure, the speed difference between normal vehicles is not large, most of them are below 3 m-s-1; low-speed driving behavior vehicles trigger the speed change of the rear vehicles, resulting in a large speed difference in many places on the road, and even reaches more than 7 m-s-1, which affects the stability of the traffic flow.

3.3. Online Identification Model Construction for Low-Speed Misfit Driving Behavior

The model was trained by the 271 case samples selected above, and the mean, standard deviation, maximum, minimum, and median values of eight feature indicators based on the vehicle's driving data and the driving fluctuation data relative to the front and rear vehicles were used as inputs and standardized. The judgment results obtained by the fuzzy comprehensive evaluation method were used as labels, and the samples were divided into a training set and a test set in the ratio of 4:1 for processing. The data imbalance problem was dealt with by using the ADASYN method and adjusting the scale pos weight parameter; the optimal values of the parameters were determined as a result of the Bayesian optimization algorithm.

To compare the effect of the model under different time windows, this paper takes 5-10s as the length of the time window and the step size is 1s, respectively, to segment the original data and train the model with the segmented data, and the number of samples used for training and the performance of the model are shown in the following table:

Table 6. Model performance analysis

Time (s)	support	form	accuracy	recall rate	F1 Score
5	263	else	0.98	0.94	0.96
	63	low-speed	0.77	0.90	0.83
6	219	else	0.97	0.94	9.94
	52	low-speed	0.78	0.87	0.82
7	175	else	0.97	0.99	0.98
	42	low-speed	0.97	0.88	0.93
8	132	else	0.97	0.98	0.98
	31	low-speed	0.93	0.87	0.90
9	88	else	0.99	0.97	9.98
	21	low-speed	0.87	0.95	0.91
10	44	else	0.98	0.95	0.97
	11	low-speed	0.83	0.91	0.87

As can be seen from the above table, the model performs best when the time window is 7s, with a precision rate of 0.97, a recall rate of 0.88, and an F1 score of 0.93 for the identification of low-speed out-of-conformity driving behavior samples. In the test set of 175 normal samples, 174 samples were identified correctly, and 1 was misclassified as a low-speed out-of-conformity sample; in the case of 42 low-speed out-of-conformity samples, 37 samples were identified correctly, and 5 samples were misclassified as normal samples.

4. Summary

This paper constructs an online identification model for low-speed misfit driving behavior based on the fuzzy comprehensive evaluation method and the XGBoost algorithm, and obtains the following main conclusions:

(1) In the calibration of low-speed uncongenial driving behavior, the introduction of eight characteristic indicators, such as the vehicle's driving data and the driving fluctuation relative to the front and rear vehicles, can be effectively determined.

(2) 23 samples of low-speed out-of-conformity driving behavior were identified among 1533 samples, and by comparing and analyzing the two types of low-speed out-of-conformity vehicle samples screened and the samples of normal driving vehicles, it can be found that the identified samples have the following phenomena: moving away from the vehicle in front and causing the vehicle behind to be affected by deceleration, resulting in significant local speed changes, which is in line with the actual traffic flow pattern; and

(3) Constructing the XGBoost online recognition model for low-speed misfit driving behavior, the precision, recall and F1 score are 97%, 88% and 93% respectively when the time window is 7s, which proves that this method can accurately identify low-speed misfit driving behavior, but there are individual other samples that will be misclassified as low-speed misfit driving behavior samples. The reason may be that the low-speed misfit driving behavior is a small probability event, and the number of low-speed misfit samples used for model training is too small, and although a series of data imbalance processing methods are used, the number of samples is still relatively small compared to the overall number of samples. The scope of the study can be expanded to obtain more samples for model training.

(4) Based on fuzzy comprehensive evaluation and machine learning algorithms, this study realizes the determination and online identification of low-speed uncongenial driving behavior, which can be used for the traffic department to regulate vehicles and maintain efficient and stable traffic flow.

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