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Choice of Lane-Changing Point in an Urban Intertunnel Weaving Section Based on Random Forest and Support Vector Machine

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ABSTRACT
Urban intertunnel weaving (UIW) section is a special type of weaving section, where various lane-changing behaviours occur. To gain insight into the lane-changing behaviour in the UIW section, in this paper we attempt to analyse the decision feature and model the behaviour from the lane-changing point selection perspective. Based on field-collected lane-changing trajectory data, the lane-changing behaviours are divided into four types. Random forest method is applied to analyse the influencing factors of choice of lane-changing point. Moreover, a support vector machine model is adopted to perform decision behaviour modelling. Results reveal that there are significant differences in the influencing factors for different lane-changing types and different positions in the UIW segment. The three most important factor types are object vehicle status, current-lane rear vehicle status and target-lane rear vehicle status. The precision of the choice of lane-changing point models is at least 82%. The proposed method could reveal the detailed features of the lane-changing point selection behaviour in the UIW section and also provide a feasible choice of lane-changing point model.

KEYWORDS
urban intertunnel weaving section; choice of lane-changing point; random forest; support vector machine.

1. INTRODUCTION

Vehicle lane-changing behaviour is a process in which drivers complete the lateral lane change after comprehensively considering information such as road conditions, traffic control measures and their own driving characteristics after developing the intention to change lanes. According to an analysed report, of the total of 5.25 million car accidents in the United States in 2020, rear-end and sideswipe accidents accounted for 27.8% and 11.8%, respectively [1]. During the lane-changing process, the object vehicle needs to continuously interact with the surrounding vehicles, and the possibility of rear-end and side-crash accidents exists. Therefore, lane-changing behaviour has also become an important factor affecting road safety and traffic efficiency. According to the motion trajectory of the vehicle, the process of lane-changing can be divided into two stages: the car-following stage to find the timing of lane-changing execution and the lane-changing stage after starting the lane-changing execution. Among them, the choice of lane-changing point is an important decision that drivers need to make before the start of the lane-changing stage. In particular, in the weaving section with limited lane-changing space, the choice of lane-changing point directly affects the safety of lane-changing behaviour and the efficiency of the weaving section [2].

Urban tunnels have the advantages of being enclosed so that they are able to resist traffic interference well, and they frequently play the role of rapidly diverting traffic flow. When the main and ground auxiliary roads between adjacent tunnels exchange traffic, an urban intertunnel weaving (UIW) section is formed, as shown in *Figure 1*. Statistics reveal that 80% of traffic accidents in urban tunnels are caused by lane-changing behaviour and 32.6% of accidents in the UIW section are lane-changing accidents [3]. The structure of the UIW section is shown in *Figure 1*.

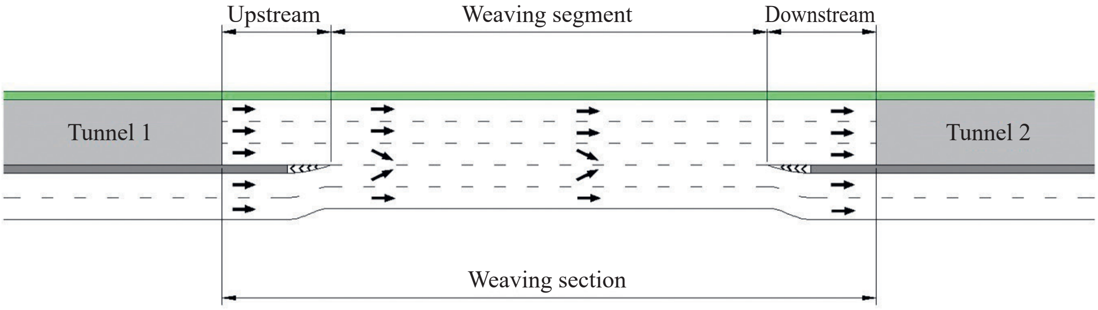

Figure 1 – Structure of an urban intertunnel weaving section

The configuration of the UIW section is similar to that of the urban expressway type A weaving section; however, in comparison, the UIW section has the following characteristics: (1) limited by the interval between the upstream and downstream intersections of the ground auxiliary roads, the length of the weaving segment of the UIW section is usually less than 300 meters and the usable interweaving space is very limited. (2) Vehicles are usually prohibited from changing lanes in urban tunnels owing to the influence of sight lines. Some vehicles that need to leave must complete continuous lane changes in the UIW section. The concentration of lane-changing behaviours has a great impact on the main road traffic. (3) The merging and diversion of the weaving section of overpasses are accomplished by setting up ramps, and traffic congestion is common near the ramps. In the limited space of the UIW section, vehicles need to be merged in and out simultaneously, resulting in a large number of lane-changing behaviours and complex interweaving behaviour, which can affect mainline traffic.

In this paper, the focus is on the lane-changing behaviour in the UIW sections. The lane-changing point selection behaviour is taken as the research object. In this work, we attempt to analyse the influencing factors of choice of lane-changing point and construct a decision model for vehicle lane-changing point selection behaviour. This research can help in understanding the lane-changing point selection behaviour and provide a method to accurately characterise the behaviour. The proposed method can be embedded into simulation models to enhance the reliability of the simulation environment.

The remainder of the paper is structured as follows: Section 2 reviews the research on lane-changing behaviour and choice of lane-changing point. Section 3 introduces data sources and processing methods. Section 4 presents the methodology used in the article and Section 5 presents the results of the study. Finally, Section 6 presents the conclusions and direction of future study.

2. LITERATURE REVIEW

Lane-changing behaviour is the focus of traffic behaviour research, and related research can be divided into three aspects: modelling lane-changing behaviour, research on influencing factors of lane-changing behaviour and the impact of lane-changing behaviour on the external environment. In terms of lane-changing behaviour modelling, in addition to traditional lane-changing behaviour models based on the cellar automata model [4], survival model [5], fuzzy logic theory [6], hidden Markov model [7], etc., machine-learning methods have been widely used in drivers' lane-changing behaviour modelling in recent years [8–10]. For example, Balal [11] compared the applicability of the fuzzy inference system, support vector machine (SVM) and multilayer feedforward (MLF) neural network to freeway drivers' lane-changing behaviour. Research on the influencing factors of lane-changing behaviour mainly divides the influencing factors into subjective factors of drivers and objective factors of the external environment. Feng [12] found that the driving style had a significant impact on lane-changing intention and lane-changing success probability and established a lane-changing behaviour model considering a driver's tendency to analyse the influence of different psychological factors on the lane-changing behaviour. Huo [13] studied the interaction between different road risk situations or angry driving styles and drivers' lane-changing behaviour. Hang [14] analysed the influence of the location of the lane-end sign and traffic volume on drivers' operation at different stages of the lane-changing behaviour through a driving simulation experiment. Furthermore, in terms of the impact of lane-changing behaviour on the external environment, Gan [15] found that the closer the lane-changing vehicle is to the work area, the more likely it is to perform dangerous lane-changing behaviours. Pan [16] simulated the queuing effect of vehicles and the diffusion of congestion caused by lane-changing behaviour to reflect the spatiotemporal impact of lane-changing behaviour on road traffic conditions. In addition, the research of Deng [17] showed that the smaller acceleration of the lane-changing vehicle means the greater speed change in the target-lane.

The construction of the lane-changing behaviour model usually includes two parts, namely, the lane-changing intention generation stage and the lane-changing execution stage [18], and the choice of lane-changing point is at the demarcation point of these two stages. In the research involving lane-changing points, the selection of lane-changing points is usually at the moment after the lane-changing intention is generated or before the lane-changing execution, which is included in the two stages of the lane-changing behaviour, rather than being an independent research object. Nilsson [19] defined the lane-changing starting and ending points through a driving simulation experiment. Moreover, Ross [20] defined lane-changing initiation as the moment when there is a lane-changing intention and the steering wheel angle is greater than 3° in an investigation of the influencing factors of distracted driving. In a natural driving experiment, Antin [21] defined the lane-changing starting point as the moment when the driver starts to turn the steering wheel or activate the turn signal. Peng [22] determined the lane-changing starting point from the lateral position of the vehicle on the lane and the rate of change of the steering wheel angle. Further, Yang [23] proposed a dynamic lane-changing path planning model, in which the lane-changing start point is judged by whether the lane-changing safety speed requirement is met. In the established lane-changing path planning model, Wang [24] defined the lane-changing starting point as the position that simultaneously satisfies the constraints of vehicle safety, power demand and passenger comfort. In the above studies on lane-changing points, the selection of lane-changing points can be summarised in two ways. One is to judge whether to start changing lanes through the driver's operation in the natural driving experiment in the process of lane-changing path planning, and the point that satisfies the constraints is considered the lane-changing starting point.

The main method of lane-changing point selection in existing studies enables the vehicle motion to satisfy the safety constraints of the lane change, while there are not enough relevant studies on lane-changing point prediction by analysis of influencing factors. Using the real lane-changing behaviour trajectory data in the UIW section, the present study intends to select the choice of lane-changing point characteristics during the lane-changing process, analyse the factors that affect the choice of lane-changing point, and construct a vehicle choice of lane-changing point model. The proposed method may be used as a new approach to studying the choice of lane-changing point.

3. DATA COLLECTION

3.1 Collection of field data

The field video was collected in Nanjing, China. The length of the UIW section captured by the video is 200 m, including the weaving segment with a total length of 120 m, and the upstream tunnel exit section and the downstream tunnel entrance section of the weaving section are both 40 m long. The road connecting the tunnels within the weaving section is the main road of the expressway (referred to as the main road in the following text), and road outside the main road is the ground auxiliary road (referred to as the auxiliary road in the following text). Both the main and auxiliary roads have three lanes in one direction and the width of each lane is 4 m. In order to take into account the rules of vehicle choice of lane-changing point under different traffic loads, the survey period was from 16:00 to 18:00 on weekdays, including some off-peak and peak hours. The collection method was unmanned aerial vehicle (UAV) video shooting, and the hovering height of the UAV was 200 m directly above the research area. To ensure a clear view, all videos were shot under good weather conditions. The vehicle trajectory data were extracted from the video by the automatic road conflict recognition system provided by the UCF Intelligent and Safe Traffic Laboratory [25], and the raw trajectory data were the pixel coordinates of the vehicle position.

An affine transformation was applied to convert the pixel coordinates into Cartesian coordinates with the vehicle's travel direction as the X-axis and the direction perpendicular to the lane as the Y-axis. The labelling method of the lane number considering the Y-coordinate and adding the information of the lane where the vehicle is located is shown in *Figure 2*. The final obtained data included time series (frame number), vehicle ID, Cartesian coordinates of vehicle position, vehicle length, vehicle type and lane ID. According to the change in the lane where the vehicle is located, the vehicle information with lane-changing behaviour during the driving process can be extracted, which can be used to study the vehicle's choice of lane-changing point. The obtained data included recorded information on 6,000 cars, which contained examples of 1,156 lane-changing behaviours. Of all the lane-changing vehicles, 42 (3.0%) were heavy vehicles and the remaining were passenger vehicles.

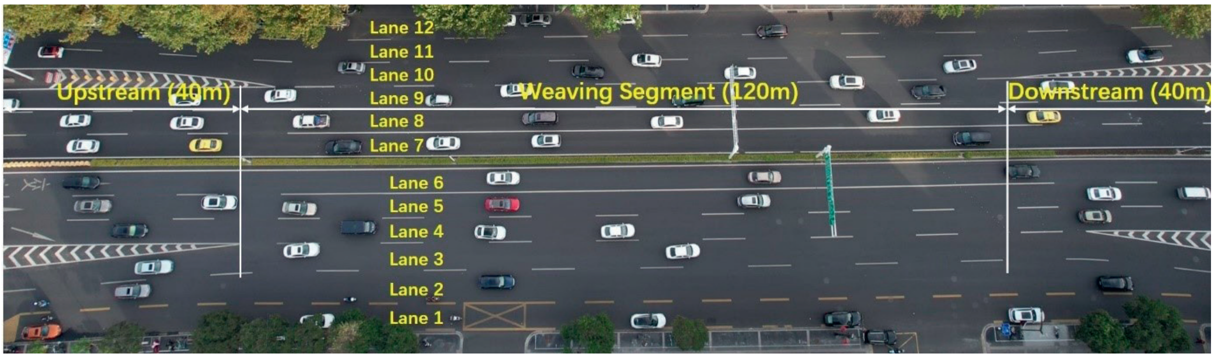

Figure 2 – Structure of the studied UIW section

3.2 Data extraction of lane-changing behaviour

The obtained data did not contain vehicle speed information; therefore, the time-averaged speed was used as the instantaneous speed of the vehicle. The time step of the data was one frame, and the velocity value directly calculated by this step had a large fluctuation range with an obvious error. By increasing the time step, referring to the study of the same research group [26], the speed value reached a stable state when the time step was five frames; thus, the corresponding speed and acceleration were calculated according to a 5 s time step.

The lane-changing point refers to the position where the vehicle makes a lane-changing decision. Because the vehicle data include the entire driving process in the weaving section, and the key data for the choice of lane-changing point include only one frame, the proportion of positive data is very low in this case. Therefore, a time window was established to reduce all vehicle trajectory data that generated lane-changing decisions. If the time window is too short, the entire process of choice of lane-changing point cannot be accurately described; if the time window is too long, the proportion of positive data used for the model will be very low, which is not conducive to model training and testing. Referring to related research [22], the maximum time window for lane-changing decision was set to 20 s. The car-following stage was at most 15 s before the appearance of the lane-changing point, and the lane-changing execution stage was at most 5 s after the appearance of the lane-changing point. If each stage was less than the maximum duration, the actual duration would be used. *Figure 3* shows the method of determining the time window for lane-changing decision. By setting the lane-changing decision time window, not only could the influencing factors related to the lane-changing decision be taken into account before and after the execution of the lane-changing decision but the proportion of positive data could also be increased.

According to driving experience and related research [27], the available gap of the target-lane directly affects the choice of lane-changing point. Therefore, relevant factors that could affect or reflect the available gap, such as surrounding-vehicle information and road traffic flow environment information, were listed as

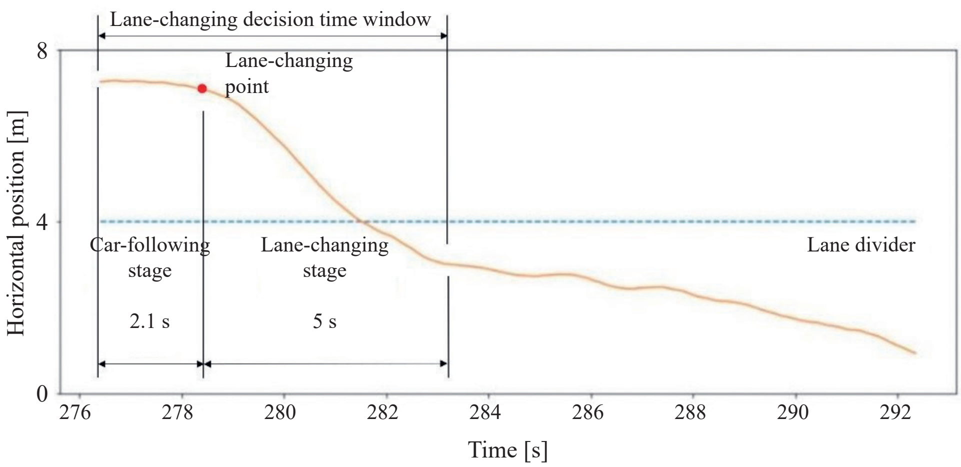

Figure 3 – Lane-changing decision time window

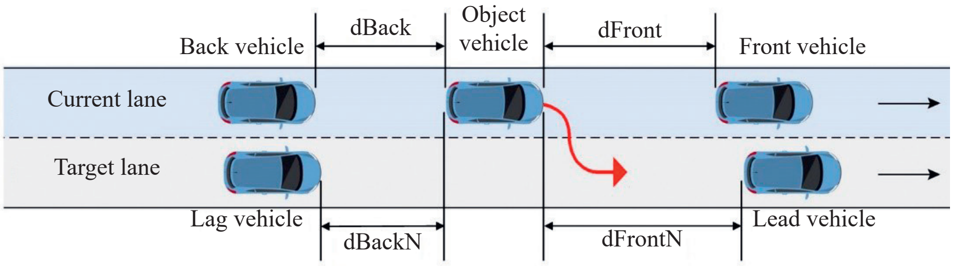

Figure 4 – Surrounding vehicles information and symbol agreement

the characteristics of lane-changing decision behaviour for this research. *Figure 4* illustrates how the distance between the object vehicle and surrounding vehicles is calculated.

Based on the determined decision time window of the lane-changing point, the road traffic flow density and lane space occupancy rate at each time step were calculated to obtain the road traffic flow information of the vehicle's lane-changing decision behaviour. Traffic flow density refers to the number of vehicles in one lane or one direction in a unit length of road section at a certain time. The space occupancy rate refers to the ratio of the total length of all vehicles to the total length of the road segment within a certain length of the observed road segment. This indicator reflects the occupancy of road space. In the case of normal traffic flow, the space occupancy rate can simultaneously represent the size of the traffic volume, and it can be used as the choice of lane-changing point for the external environment affecting the vehicle. *Table 1* presents a dataset of choice of lane-changing point behaviour, which shows the basic vehicle information and the names and meanings of the 13 lane-changing decision features that were used in subsequent research.

Table 1 – Vehicle information and features of choice of lane-changing point

Feature name	Feature description	Feature name	Feature description
FrameNum	Number of time series (1/30 s)	dBack	Gap with rear vehicle [m]
CarID	Number of object vehicle	vBack	Velocity of rear vehicle [m/s]
xCen	x-coordinate of vehicle centre [m]	dFront	Gap with leading vehicle [m]
yCen	y-coordinate of car centre [m]	vFront	Velocity of leading vehicle [m/s]
Lane	Number of current-lane (1–12)	dBackN	Gap with rear vehicle on target-lane [m]
LaneN	Number of target-lane (1–12)	vBackN	Velocity of rear vehicle on target-lane [m/s]
Velocity	Velocity of object vehicle [m/s]	dFrontN	Gap with leading vehicle on target-lane [m]
Acceleration	Acceleration of object vehicle [m/s^2]	vFrontN	Velocity of leading vehicle on target-lane [m/s]
LcFlag	Whether lane changed (0=No, 1=Yes)	Occupancy	Spatial occupancy of current-lane
Density	Density of UIW section [veh/km]	OccupancyN	Spatial occupancy of target-lane

4. METHODOLOGY

4.1 Feature selection by random forest

In the UIW section, weaving behaviours affect the order of vehicles in the weaving section. The difference between the location of the lane-changing vehicle and the driving environment will affect the driver's choice of lane-changing point, resulting in different lane-changing decision behaviours. Based on the traffic situation of the investigated section, the lane-changing decision behaviour is classified mainly from two aspects – the purpose of lane-changing and the position of the lane-changing point, to improve the accuracy of the decision model of the lane-changing point [28].

The lane-changing purpose is mainly aimed at the change of lanes, and the lane-changing decision behaviours in the UIW section are mainly divided into four categories: the mandatory lane-changing movement from the main road to the auxiliary road and the auxiliary road to the main road, and the discretionary lane-changing behaviour within the main road and the auxiliary road. The choice of lane-changing point dataset was divided into four sample sets according to the difference in the lane-changing purpose.

Because there were only 1,156 lane-changing vehicles, the number of lane-changing vehicles in the four classified sample sets was limited, and their distribution was sparse in the 200 m weaving section; thus, it was unsuitable for continuous choice of lane-changing point research. Therefore, in this work, the weaving section was segmented, the four sample sets were further divided into 10 sample subsets at 20 m intervals, and the feature selection and modelling of choice of lane-changing point were performed. *Table 2* presents the classified lane-changing point data according to lane-changing vehicles' purpose and position.

Table 2 – Lane-changing point data classified by different purposes and positions

	Seg1	Seg2	Seg3	Seg4	Seg5	Seg6	Seg7	Seg8	Seg9	Seg10	Sum
Main–Main	46	24	44	29	26	7	9	5	0	0	190
Main–Aux	47	33	53	76	47	24	22	15	0	0	317
Aux–Main	11	11	78	64	33	31	20	13	0	0	261
Aux–Aux	69	20	89	42	49	64	26	24	5	0	388
Sum	173	88	264	211	155	126	77	57	5	0	1156

For the multifeature lane-changing decision behaviour dataset, accurately selecting the feature combination that affects the lane-changing decision behaviour can improve the training efficiency and accuracy of the choice of lane-changing point model. The random forest (RF) model can be applied to binary classification problems such as lane-changing decision (the result is only *yes* or *no*), and the RF model can filter features by outputting variable importance measures (VIMs) to obtain better feature combinations. The VIM is usually obtained using the Gini index or out-of-bag (OOB) error rate. Because of the uneven distribution of samples, the number of no lane changes (LcFlag=0) is larger than that of lane changes (LcFlag=1), in which case the VIM obtained from the OOB error rate would be underestimated. Therefore, in this work, the VIM score was calculated using the Gini index.

4.2 Lane-changing decision model by support vector machine

In this study, various methods including backpropagation (BP) neural network, gradient boosting, decision tree (classification and regression tree, CART) and SVM were tested for prediction modelling of the choice of lane-change point. However, owing to the limited data size of 1,156 lane-changing vehicles, only the SVM model could achieve a relatively acceptable prediction result. Therefore, SVM was selected to model the decision behaviour.

SVM is a binary classification model that can correctly divide the training set and maximise the geometric interval. When faced with linear problems, SVM maximises the classification interval through an optimisation algorithm. To nonlinear problems, the input features are mapped into the high-dimensional feature space by introducing an appropriate kernel function, so that the high-dimensional feature space is linearly separable, and the conversion between nonlinear and linear problems is completed. In the new feature space, the optimisation algorithm is used to establish an optimal linear classification surface, and the classification samples are obtained.

As an SVM-based classification model, support vector classification (SVC) has some advantages when dealing with two types of label classification tasks. The SVC-based choice of lane-changing point model presented herein is a two-class model (the choice of lane-changing point is Yes-True, and the choice of lane-changing point is No-False). The output was whether to change lanes. If the result of prediction was that the lane change is completed at a certain point in the UIW section, "1" is the output, otherwise "0" is the output. By calculating the ratio of the number of choices of lane-changing points to the total number in the dataset, the probability that the lane-changing points of different lane-changing purposes fall in all intervals of the weaving section are obtained, which is used to visualise the results of the SVC model.

Precision, recall, accuracy and F_1 value, which are common in binary classification problems, were selected as evaluation indicators. Because of the difference in the number of positive and negative examples of lane-changing decisions, the accuracy of the model is generally high. Therefore, the model is mainly evaluated in terms of precision and recall.

5. RESULTS AND DISCUSSION

5.1 Feature selection of choice of lane-changing point

Distribution characteristics of lane-changing point

Taking the driving direction as the horizontal axis and the lane as the vertical axis, a scatter plot was drawn for all the lane-changing points in the entire weaving section (the Cartesian coordinate range was 160–360 m). Furthermore, an interval of 20 m was used to draw the heat map of the vehicle lane-changing point position distribution for the heat of the lane-changing points of each lane. The scatter diagram and heat map are shown in *Figure 5*.

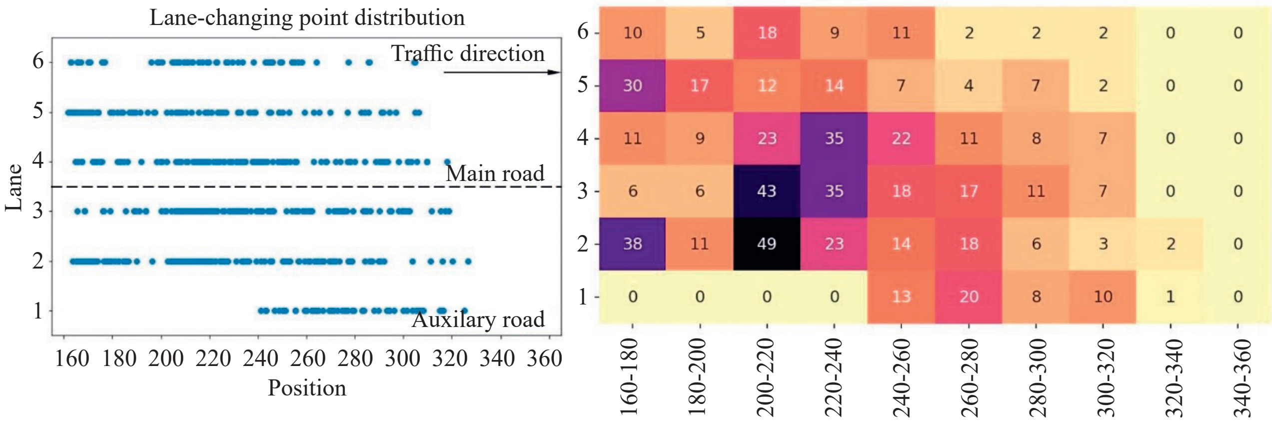

Figure 5 – Distribution scatter diagram and heat map of lane-changing point

Based on the analysis of the actual situation on the road, the distribution of lane-changing points in the UIW section has the following rules.

1) Because of the physical isolation within 40 m upstream of the weaving section, vehicles can only change lanes within the main or auxiliary road, mainly in lanes 2 and 5. After entering the weaving segment at 200 m, lane-changing behaviour is allowed between the main and auxiliary roads, and a large number of mandatory lane-changing behaviours occur. Lane-changing behaviours are concentrated in lanes 2, 3 and 4, and the number of lane-changing behaviours gradually decreases with the direction of traffic flow; after reaching the downstream of the weaving section at 320 m, almost no lane-changing points occur.
2) The starting point of the weaving segment is the burst point of the mandatory lane-changing decision behaviour and then it begins to spread to the direction and side of the traffic flow. By contrast, at the end of the weaving segment, there is no secondary burst of lane-changing decision behaviour caused by approaching the end zone of the mandatory lane-changing. Downstream of the weaving section, the number of lane-changing points for each lane is almost zero.
3) The innermost lane of the main road (lane 6) and the outermost lane of the auxiliary road (lane 1) have fewer lane-changing points. Among them, in lane 6, because the lane marking line turns into a solid white line after entering the weaving segment and lane-changing behaviour is usually prohibited, there is almost no lane-changing behaviour in the second half of the weaving section. Lane 1 is a bus lane with less traffic volume and less lane-changing behaviour.

Analysis of influencing factors of choice of lane-changing point

For any sample subset, a total of 13 decision features – velocity, acceleration, vFront and vBack, dFront and dBack, vFrontN and vBackN, dFrontN and dBackN, occupancy and occupancyN and density were used to complete the RF model construction, and the modelling of all sample subsets was completed independently. In the modelling process, the grid search method was used to automatically adjust the parameters to obtain the optimal parameters of the RF model; then, the model construction and training were completed. *Table 3* presents the selected best parameters.

Table 3 – Best parameters of RF

Parameters	Best value
n estimator	455
max depth	3
min sample split	140
min sample leaf	70
max feature	3

To improve the applicability of the feature, for any sample subset, the 13 VIM scores obtained are arranged in descending order, and the initial feature combination is defined as the three features with the highest VIM scores. On this basis, each iteration increases the unselected feature with the highest VIM score and runs the RF model in a loop until all features are added. In this process, the accuracy of the model output results is compared, and the feature combination contained in the model with the highest accuracy is the optimal feature combination corresponding to the training subset. *Figure 6* shows the sorted feature importance of a sample subset; in this case, the initial feature combination comprises dBackN, acceleration and vBack.

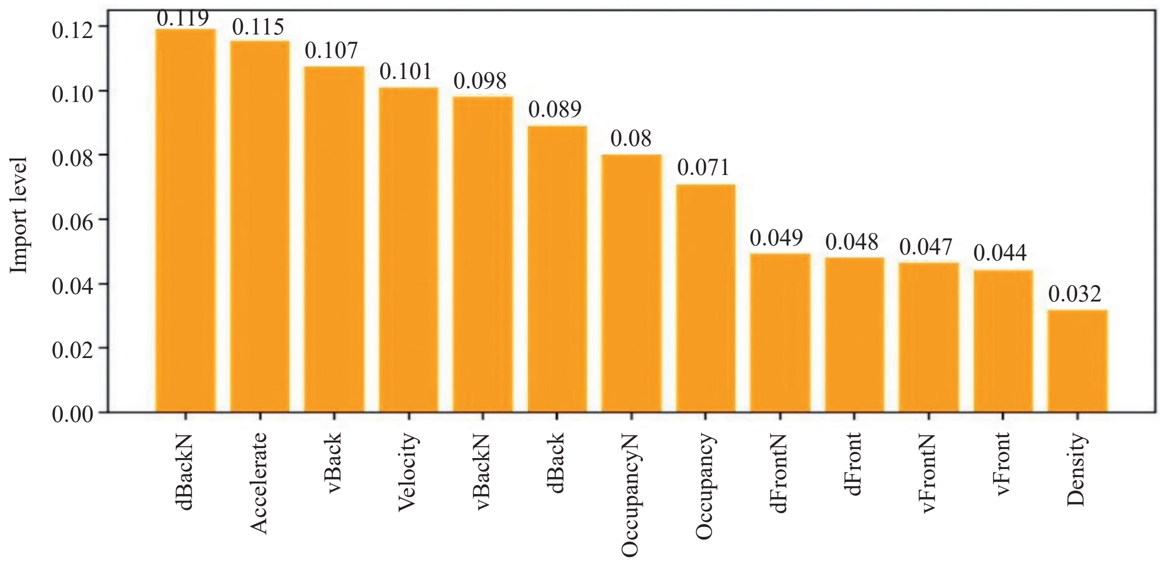

Figure 6 – Feature importance of choice of lane-changing point for one sample subset

Furthermore, to summarise the influence of different features on the choice of lane-changing point, all features of lane-changing decision behaviours are divided into eight categories: object vehicle status (velocity and acceleration), current-lane leading vehicle status (velocity and gap), current-lane rear vehicle status (velocity and gap), target-lane leading vehicle status (velocity and gap), target-lane rear vehicle status (velocity and gap), current-lane status (occupancy), target-lane status (occupancy) and system status (density). *Figure 7* shows the extraction results of the key feature combinations of four types of lane-changing decision behaviours with different lane-changing purposes.

Each row in *Figure 7* represents a certain type of lane-changing decision behaviour on the specified segment, i.e. a sample subset. The column name of cells marked with "●" in the row denotes the optimal feature combination of the sample subset. Combined with *Figure 7*, the key feature radar charts of the four categories of lane-changing decision behaviours are drawn in *Figure 8*.

Combining *Figures 7 and 8*, we conclude the following.

1) For all choice of lane-changing point behaviours in the UIW section, the ranking of the influence degree of the eight types of choice of lane-changing point features in decreasing order is as follows: object vehicle status, target-lane rear vehicle status, current-lane rear vehicle status, target-lane leading vehicle status, current-lane leading vehicle status, target-lane status, current-lane status, system status. Among them, an intuitive understanding of the system status (density) is difficult to achieve for the driver; thus, the judgment of the traffic flow density usually relies on the lane status and surrounding-vehicle status, so the system status can scarcely affect the selection of lane-changing point. Thus, the object vehicle status, current-lane rear vehicle status and target-lane rear vehicle status are the three most influential features in all choice of lane-changing point behaviours.
2) In Main–Aux, the target-lane rear vehicle status is the most significant lane-changing feature, followed by the current-lane rear vehicle status and object vehicle status, and their degrees of influence are close. From *Figure 8*, the current-lane status and target-lane leading vehicle status are found to have little influence on the decision of the lane-changing point in the second half of the weaving section.
3) The influencing factors of Aux–Main are similar to those of Main–Aux and also most affected by the target-lane rear vehicle status. The difference is that the influence of the current-lane rear vehicle status and object vehicle status decreases, while that of the target-lane status increases.
4) The main feature of Main–Main is the object vehicle status; current-lane status and target-lane status have little influence on the lane-changing point selection, and the system status has no effect on the choice of lane-changing point.
5) In Aux–Aux, the object vehicle status has the highest degree of influence, while the system status does not affect the choice of lane-changing point. The other features such as lane status and surrounding-vehicle status are of similar importance. Furthermore, from *Figure 8*, in the first half of the weaving section, the choice of lane-changing point is mainly affected by the speed and acceleration of the object vehicle and less affected by the surrounding vehicles.

Lane-change type	Segment	Object vehicle status		Target-lane rear vehicle status		Current-lane rear vehicle status		Target-lane leading vehicle status		Current-lane leading vehicle status		Target-lane status	Current-lane status	System status
		Velocity	Acceleration	vBackN	dBackN	vBack	dBack	vFrontN	dFrontN	vFront	dFront	OccupancyN	Occupancy	Density
Main-Aux	1	—	—	—	—	—	—	—	—	—	—	—	—	—
	2	●				●	●		●		●	●		
	3	●		●	●			●				●		
	4	●	●	●	●		●	●		●	●			
	5	●	●	●		●		●	●	●				
	6			●	●	●	●		●			●		
	7		●	●	●	●	●							
	8	●		●	●									
	9	●	●	●	●	●	●					●	●	
	10	—	—	—	—	—	—	—	—	—	—	—	—	—
Aux-Main	1	—	—	—	—	—	—	—	—	—	—	—	—	—
	2				●	●	●		●		●	●		
	3	●		●	●			●				●		
	4		●	●	●						●			
	5	●		●	●								●	
	6	●			●	●						●		
	7		●	●	●		●				●	●		
	8		●	●			●					●		
	9	●	●	●	●	●	●					●	●	●
	10	—	—	—	—	—	—	—	—	—	—	—	—	—
Main-Main	1	●	●		●			●	●	●	●	●	●	
	2	●	●	●		●		●	●	●			●	
	3	●	●	●		●		●	●	●	●		●	
	4	●	●	●	●			●		●				
	5	●	●	●	●			●	●					
	6	●	●	●	●		●			●	●		●	
	7	●	●	●	●	●	●		●	●	●	●		
	8	●	●			●								
	9	●	●	●		●	●							
	10	—	—	—	—	—	—	—	—	—	—	—	—	—
Aux-Aux	1	—	—	—	—	—	—	—	—	—	—	—	—	—
	2	●					●	●	●				●	
	3	●	●					●	●	●				
	4	●	●							●				
	5	●	●					●					●	
	6	●		●	●							●		
	7	●	●	●	●	●	●		●		●	●	●	
	8	●	●	●	●	●	●	●		●		●	●	
	9	●	●	●	●	●	●					●		
	10	—	—	—	—	—	—	—	—	—	—	—	—	—
Sum		**27**	**23**	**23**	**23**	**16**	**15**	**13**	**12**	**11**	**10**	**16**	**11**	**1**
		50		**46**		**31**		**25**		**21**		**16**	**11**	**1**

Figure 7 – Optimal feature combinations for different sample sets

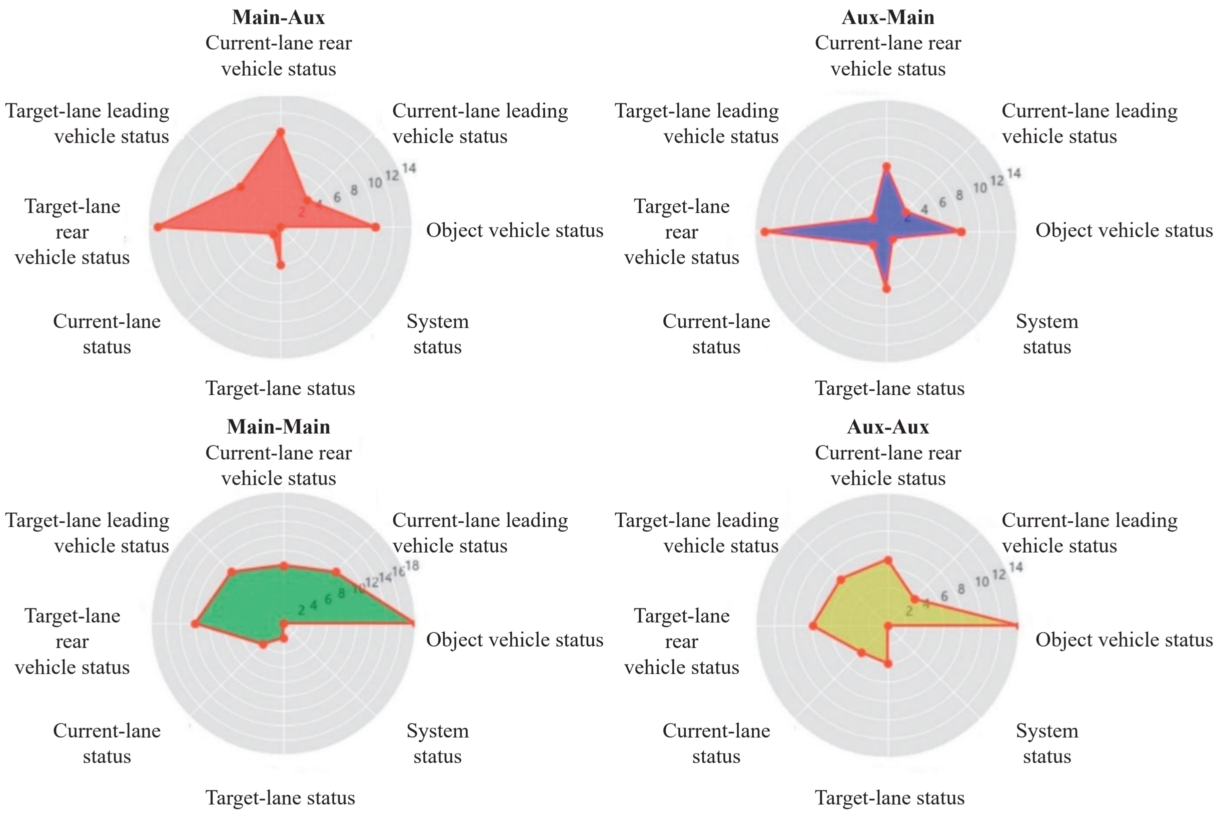

Figure 8 – Radar diagrams of choice of lane-changing point features with different lane-changing purposes

6) Comparison of the two types of mandatory choice of lane-changing point behaviours reveals that both have four significant types of feature combinations, and the lane-changing of Main–Aux contains two more types of decision features other than the lane change of Aux–Main, that is, current-lane leading vehicle status and target-lane leading vehicle status. Furthermore, comparison of the two types of discretionary lane-changing decisions indicates that the influence degree of each feature is similar. Compared with the auxiliary road, the discretionary lane-changing behaviour inside the main road is more affected by the leading vehicle. Considering the actual situation on the road, the driving speed on the main road is higher than that on the auxiliary road. Thus, when changing lanes, the state of not only the rear vehicle but also the leading vehicle must be considered.

5.2 Modelling decision behaviour based on SVM

The dataset was constructed using the results shown in *Figure 7* and only contained the features filtered by RF. Taking Main-Aux as an example, the features contained in the subset of segment 2 are velocity, vBack, dBack, dFrontN, dFront and occupancyN. The dataset was divided into 70% training samples and 30% test samples, and the SVM model was constructed for each type of lane-changing decision behaviour. *Figure 9* shows the learning curve of SVC, and the model parameters of SVC model are listed in *Table 4*.

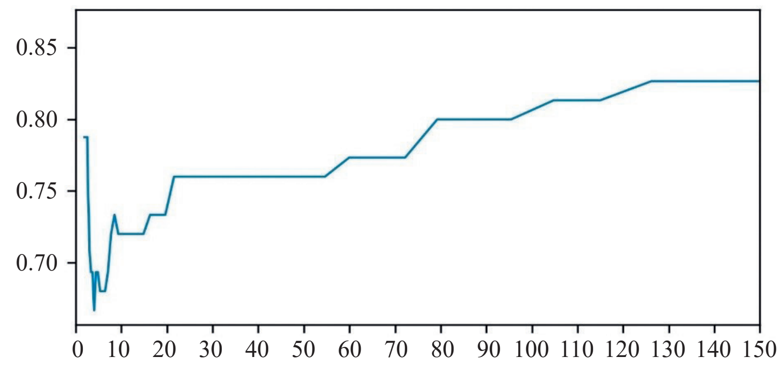

Figure 9 – Learning curve of SVC

Table 4 – SVC model parameter settings

Parameters	Values
Kernel	$rbf = k(x,x') = e^{-\frac{\lVert x-x' \rVert^2}{2\sigma^2}}$
C	50
Gamma	Auto
max iter	10,000
shrinking	True

The SVC model was used to predict the lane-changing decision behaviour of each lane-changing type at the lane-changing points in different sections, the prediction results were counted, and the evaluation index and lane-changing probability were calculated. The confusion matrix of the model is statistically presented in *Table 5*. *Figure 10* presents the probability distribution of the choice of lane-changing point of the four types of data, and *Table 6* lists the evaluation indicators of the model prediction result.

From the prediction results of different types of choices of lane-changing points in the UIW section obtained using the comprehensive analysis model, combined with the actual operation of traffic flow, the following conclusions can be drawn.

Table 5 – Confusion matrix of model output

	TP	FP	FN	TN	Total
Main–Aux	39	8	12	890	949
Aux–Main	28	4	8	743	783
Main–Main	25	3	5	536	569
Aux–Aux	44	10	13	1102	1167

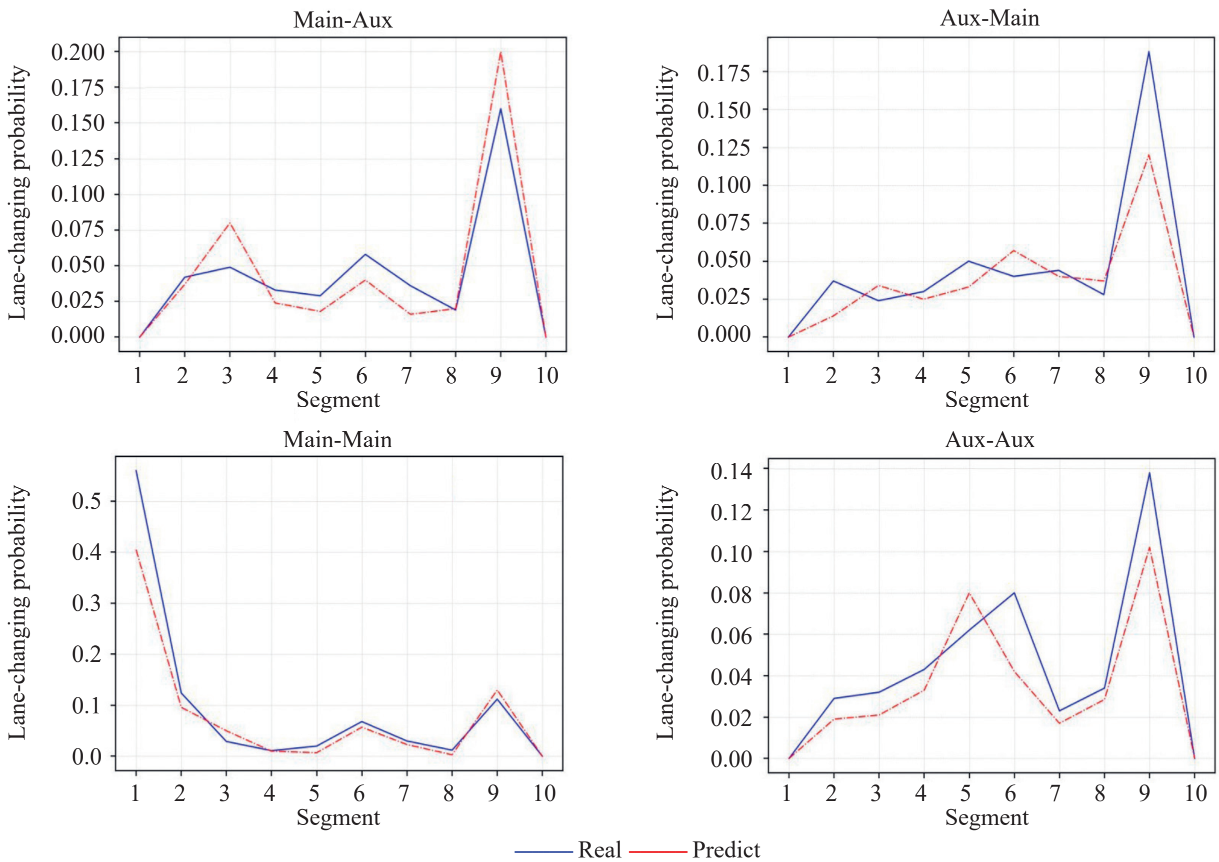

Figure 10 – LC initial point probability distribution curve

Table 6 – Evaluation indicators of model predictions

Model	Precision	Recall	Accuracy	F_1
Main–Aux	0.8298	0.7647	0.9789	0.7959
Aux–Main	0.8750	0.7777	0.9846	0.8235
Main–Main	0.8928	0.8333	0.9859	0.8320
Aux–Aux	0.8461	0.7719	0.9820	0.8072

1) The lane-changing probability distribution trends of various types of data predicted using the RF and SVM models are essentially the same, and the lane-changing behaviour probability distribution within the main road is best predicted. The prediction of the lane-changing decision behaviour in sections using the SVC model and the results obtained by calculating the probability values of the lane-changing points in each segment are consistent with the actual traffic conditions.
2) Precision, recall, accuracy and F_1 are used as the evaluation indicators of the model. The precision of the four types of data is greater than 82%, and the recall is at least 76%. The model constructed using SVC can approximately realise the task of lane-changing point prediction.

6. CONCLUSIONS

In this work, we considered the UIW section as the background and focused on the choice of lane-changing point behaviour during the lane-changing process. Through aerial photography and image recognition technology, the trajectory data of lane-changing vehicles and the surrounding vehicles were collected. The RF model was used to analyse the influencing features of the lane-changing decision for four different lane-changing purposes. In addition, the SVC model was used to construct the decision models of four types of lane-changing behaviours. Indicators such as precision, recall, accuracy and F_1 value were selected to evaluate the applicability of the choice of lane-changing point model. The following conclusions can be drawn from this research.

1) Lane-changing points before the weaving segment are mainly concentrated in the middle lanes of the main road and the auxiliary road. After entering the weaving segment, the number of lane-changing points on the two adjacent lanes of the main road and the auxiliary road increased rapidly. Then, the lane-changing points spread along the direction of traffic flow and the side lanes. Simultaneously, at the end of the weaving segment, there is no secondary burst in the number of lane-changing points caused by approaching the end of the lane-changing area.
2) Among the features affecting the choice of lane-changing point, object vehicle status, current-lane rear vehicle status and target-lane rear vehicle status are the three most important features, while system status has little effect on the choice of lane-changing point. There are significant differences in the influencing factors for the four types of choice of lane-changing point behaviours, and the influencing factors for the same type of lane-changing behaviour at different positions in the weaving section are not identical.
3) Models based on RF and SVM can approximately predict the lane-changing points. The precision of the tested models is greater than 82%, and the recall is at least 76%.

From this study, several future research elements can be identified: (1) because of the difficulty in data collection and extraction, the scale of data used in this study was limited, which limited the level of sophistication in decision modelling. (2) The lane-changing behaviour in the weaving section could also be divided into overtaking lane-changing behaviour, continuous lane-changing behaviour and other types according to the behaviour characteristics, making the selection of the lane-changing point more complicated. In the future, more in-depth modelling research of choice of lane-changing point under different types of lane-changing behaviours is required.

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基于随机森林和支持向量机的城市连续隧道交织区换道点决策

摘要：
城市连续隧道交织区是一种具有多种换道行为的特殊交织区。为了深入了解城市连续隧道交织区中的换道行为，本文尝试从换道点选择的角度分析换道决策特征，并对换道决策行为进行建模。根据现场采集的换道轨迹数据，将换道行为分为4种类型。采用随机森林分析影响换道点决策的因素。此外，采用支持向量机模型进行决策行为建模。结果表明：在城市连续隧道交织区内，不同换道类型和不同位置的换道决策影响因素存在显著差异;三个最重要的因素类型分别是当前车辆状态、当前车道后方车辆状态和目标车道后方车辆状态。建立的换道点决策模型的精度至少为82%。该方法可以揭示城市连续隧道交织区内换道点选择行为的详细特征，并提供可用的换道点决策模型。

关键词：
城市连续隧道交织区；换道点决策；随机森林；支持向量机