Research Article

Research on the Prediction of the Operational Risk Field of Intelligent Vehicles Based on Dual Multiline LiDAR

Ruibin Zhang,1,2 Yingshi Guo,1 Chang Wang,1 Yang Zhou,1 and Yunze Long2

1School of Automobile, Chang’an University, Xi’an 710064, China
2School of Automobile Engineering, Guilin University of Aerospace Technology, Guilin 541004, China

Correspondence should be addressed to Yingshi Guo; guoys@chd.edu.cn

Received 30 November 2021; Accepted 24 February 2022; Published 23 March 2022

Copyright © 2022 Rubin Zhang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

To effectively evaluate the risk situation between intelligent vehicles and surrounding traffic participants in complex scenes, a complex traffic environment perception technology based on dual multiline light detection and ranging (LiDAR) is proposed in this work. The vehicle motion state is predicted by fusing the multiview characteristics of point cloud timing and multitarget interaction information, and the risk assessment model is constructed via artificial potential field theory. The real-time point cloud information is used to obtain the time-sequence bird’s-eye view and range image. The improved VGG19 network model is used to extract the time-sequence high-level abstract combined features in the multiview scene. The constructed time-sequence feature vector is used as the input data of the attention mechanism, and the attention-bidirectional long short-term memory (Attention-BiLSTM) model is used for training to form the desired input-output mapping relationship. The motion state of the target vehicle can therefore be updated, and the static and dynamic risk fields of traffic participants surrounding the vehicle can be established based on artificial potential field theory, thereby allowing for the evaluation of the operational risk of the intelligent vehicle. The results of experiments demonstrate that the prediction effect of the target vehicle state parameters via the use of the proposed model is better than that of other compared models, and the prediction effect of the risk field of intelligent vehicle operation based on the multiview point cloud features and vehicle interaction information is good.

1. Introduction

The modeling of the traffic situation of a road environment is a key technical means to ensure the safe driving of intelligent vehicles in the road area and prevent rollover and collision and has therefore attracted extensive research attention. Traffic risk prediction is mainly used to process original sensor data, which usually include the lowest-level data from stereo vision [1], radar [2], and light detection and ranging (LiDAR) [3] systems. With the help of these sensor data, models can reasonably and simply express the surrounding environment of the vehicle, the main information of which includes the location information of the boundaries (lane line, roadside, and intersection) and information about obstacles in the road. The ultimate goal is to improve traffic safety and reduce the incidence of traffic accidents.

At present, the most common risk assessment method is to establish the risk field model via a grid map or the artificial potential field method. A grid map model is a variant of the Bayesian occupancy filter [4]. In the field of intelligent vehicles, occupancy grids based on Bayesian occupancy filter theory have been widely applied in various studies [5–9]. For example, Lee and Kum [10] proposed a risk assessment method for the prediction of an occupancy map and combined this method with acceleration trajectory sampling and screening to obtain the safe trajectory with the lowest risk. Khatib [11] proposed the establishment of the risk field model by using the artificial force field method; the core concept is that the
obstacle generates a repulsive field, the target point generates a gravitational field, and a robot moves along the direction with the fastest decline of the potential field in the combined potential field. At present, the common method used in the field of decision planning is to establish the repulsion fields of roads, lane lines, and obstacle vehicles and the gravitational field of target points and to solve the potential field parameters according to the vehicle driving trajectory [12–17]. Hesse and Sattel [18] combined the potential field method and elastic belt theory, introduced vehicle dynamics into the elastic belt, and ultimately proposed an extended elastic belt path-planning method. Cheng et al. [19] introduced a virtual force field and proposed an obstacle avoidance path-planning method based on model prediction theory, which exhibited good robustness. Tang et al. [20] proposed the RRT* algorithm guided by the safety field, which is characterized by a reduced amount of calculation and an improved convergence speed. Parzani and Filbet [21] proposed a local path-planning algorithm for active collision avoidance based on a dangerous repulsion field, which is characterized by a small amount of computation, safety, and reliability. Song et al. [22] improved the traditional artificial potential field method and established an objective function that considers both road and vehicle constraints; this not only eliminates the problem of jitter, but also meets the safety index requirement. To overcome the problem of the local minimum points of the artificial potential field, researchers have proposed some improved methods, such as the general potential field method and virtual force field method [23–25], the artificial coordination field [26–30], the random escape method [31], heuristic search and walking along the wall [32], and the tangent bug method [33], among others. These methods have generally been proposed to apply additional control force to the controlled object. The controlled object is generally a robot and usually has no road constraints; thus, it is unsuitable for path planning under structured road conditions. The future motion state of traffic participants surrounding the target is affected by the motion of other objects and the spatial environment. Thus, in view of these problems and the complexity of urban scenes, to improve the prediction accuracy of the risk field of intelligent vehicle operation, it is necessary to analyze the interaction relationship between multiple objects and the information above and below the scene. Because the motion of an object in an urban scene is affected by the interaction of other surrounding objects and the surrounding environment, in this work, our contributions are mainly given by the following:

(1) Propose an environment sensing technology based on dual multiline LiDAR to effectively collect the surrounding environment of intelligent vehicles and the interaction information with traffic participants in complex traffic scenes.

(2) Establish a multiojective operation interaction feature model based on one-dimensional convolutional neural network to effectively mine the interaction features in vehicle operation state parameters.

(3) Two improved VGG19 network models are used to extract the dual view features of point cloud so as to provide necessary high-precision environmental spatiotemporal information input for moving target state prediction.

(4) Integrate the multiview features of point cloud timing and multitarget interaction information obtained by dual multiline LiDAR, and effectively evaluate the risk situation between intelligent vehicles and surrounding traffic participants in complex scenes by using the Attention-BiLSTM model.

2. Dual Multiline LiDAR Environment Sensing System

To effectively collect information on the surrounding environment of intelligent vehicles and information on interactions with traffic participants in complex traffic scenes, an environment sensing technology based on dual multiline LiDAR is proposed. The installation position of the dual multiline LiDAR system is illustrated in Figure 1. The vertical installation mode is adopted for the LiDAR system. The LiDAR on the upper side is used to obtain the global environmental map information in real time and generate the time-sequence aerial view and front-view depth map point clouds. The LiDAR located at the lower side is used to detect the operation status data of traffic participants in real time and obtain information on the complex interactions between the intelligent vehicle and traffic participants.

The mathematical model of the installation position of the dual multiline LiDAR system is as follows:

\[
\begin{align*}
    d_i &= h_1 \times \tan(a_1 + i \times \Delta \phi_1) \\
    d_i &= h_1 \times \tan(a_1 + i \times \Delta \phi_1) \\
    d_1 &= h_1 \times \tan(a_1) \\
    d_i &= h_1 \times \tan(a_i)
\end{align*}
\]

where † represents the LiDAR on the upper side of the dual LiDAR system, ‡ represents the LiDAR on the lower side of the dual LiDAR system, \( h \) is the height of the center point of the LiDAR relative to the ground, \( \alpha \) is the included angle between the horizontal line of the LiDAR center and the lowest scanning line, \( \Delta \phi \) is the vertical angular resolution of the LiDAR, \( d \) is the distance between the ground intersection of the lowest scanning line and the ground projection point of the LiDAR center, and \( d_i \) is the projection distance of the scanning line above the \( i \)th horizontal plane of the LiDAR on the ground [34].

When working, the LiDAR shall ensure that it will not scan the red key points of the vehicle body. Point \( A' \) is located at the front end of the hood, point \( B' \) and point \( C' \) are the lowest and highest points of the \( A \)-pillar of the vehicle frame, respectively, point \( D' \) and point \( E' \) are the
highest and lowest points of the C-pillar of the vehicle frame, respectively, and point $F'$ is the rearmost end of the trunk. $A'$ and $A''$, $B'$ and $B''$, $C'$ and $C''$, $D'$ and $D''$, $E'$ and $E''$, and $F'$ and $F''$ are symmetrical about points $A$, $B$, $C$, $D$, $E$, and $F$, respectively. Take the projection point $O$ of point $F$ on the ground plane as the origin of the coordinate system, take $O$ as the starting point, point to the front of the vehicle along the ground plane in the longitudinal central plane as the positive direction of $X$-axis, the vertical longitudinal central plane of crossing point $O$ points to the driver’s side as the positive direction of $Y$-axis, and the vertical ground plane of crossing point $O$ points to the vehicle body as the positive direction of $Z$-axis. 32-line LiDAR center point coordinates are $(x_1, y_1, z_1)$; 16-line LiDAR center point $G_1$ coordinates are $(x_1, y_1, z_1)$. In order to ensure that key points $A$, $B$, $C$, $D$, $E$, and $F$ are not in the field of vision of dual LiDAR, taking 32-line LiDAR as an example, the installation coordinates shall meet the following requirements:

\[
\begin{align*}
  z_A &< \tan \alpha_1(x_A - x_1) + z_1 \\
  z_B &< \tan \alpha_1(x_B - x_1) + z_1 \\
  z_C &< \tan \alpha_1(x_C - x_1) + z_1 \\
  z_D &< \tan \alpha_1(x_D - x_1) + z_1 \\
  z_E &< \tan \alpha_1(x_E - x_1) + z_1 \\
  z_F &< \tan \alpha_1(x_F - x_1) + z_1
\end{align*}
\]

In order to prevent the lateral key points $A'$, $B'$, $C'$, $D'$, $E'$, and $F'$ of the vehicle from being scanned by the LiDAR, the installation of the LiDAR position shall also meet the following requirements:

\[
\begin{align*}
  \cot \alpha_1(z_1 - z_A') &\geq \sqrt{(x_1 - x_A')^2 + (y_1 - y_A')^2} \\
  \cot \alpha_1(z_1 - z_B') &\geq \sqrt{(x_1 - x_B')^2 + (y_1 - y_B')^2} \\
  \cot \alpha_1(z_1 - z_C') &\geq \sqrt{(x_1 - x_C')^2 + (y_1 - y_C')^2} \\
  \cot \alpha_1(z_1 - z_D') &\geq \sqrt{(x_1 - x_D')^2 + (y_1 - y_D')^2} \\
  \cot \alpha_1(z_1 - z_E') &\geq \sqrt{(x_1 - x_E')^2 + (y_1 - y_E')^2} \\
  \cot \alpha_1(z_1 - z_F') &\geq \sqrt{(x_1 - x_F')^2 + (y_1 - y_F')^2}
\end{align*}
\]

2.1. Multiview Point Cloud Generation. The detection accuracy in complex environments is low due to the lack of depth information of images collected by a camera. Although the original point cloud obtained by LiDAR has accurate depth information, the point cloud is sparse and can only realize the three-dimensional (3D) frame positioning of large objects. The detection effect of small objects is poor and is prone to missed detection or false detection. In the aerial view of the original point cloud obtained by transformation, the objects occupy different spaces, which can avoid the occlusion problem between objects. Moreover, the 3D boundary of the object in the aerial view is accurate, which can avoid the problem of position offset, and the projection object in the aerial view retains its physical size, which can avoid the problem of object distortion. The depth information of the area in front of a moving object can be obtained from the front-view depth map obtained by the
The multiview generation process of the point cloud is used to convert the original LiDAR point cloud into a top aerial view and a front depth view, as presented in Figure 2.

The bird’s-eye view and range image can be obtained by transforming the original point cloud of 3D LiDAR via the two-dimensional (2D) projection of a 3D image and according to the internal parameters of the corresponding camera. The conversion relationship from the LiDAR coordinate system to the image coordinate system is as follows:

\[
\begin{bmatrix}
    u \\
    v \\
    1
\end{bmatrix} =
\begin{bmatrix}
    1 & 0 & u_0 \\
    0 & 1 & v_0 \\
    0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
    f & 0 & 0 \\
    0 & f & 0 \\
    0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
    R_{L-C} & T_{L-C} \\
    0^T & 1
\end{bmatrix}
\begin{bmatrix}
    X_L \\
    Y_L \\
    Z_L
\end{bmatrix},
\]

where \((u, v)\) is the pixel coordinate, \((X_C, Y_C, Z_C)\) is the camera coordinate, \((X_L, Y_L, Z_L)\) is the LiDAR coordinate, \(R_{L-C}\) represents the rotation matrix from the LiDAR coordinate system to the camera coordinate system, and \(T_{L-C}\) represents the 3D translation vector from the LiDAR coordinate system to the world coordinate system. Moreover, \(u_0\) and \(v_0\) are the internal parameters of the camera, \(f\) is the focal length of the camera, and \(Z_C\) is the depth value corresponding to the current image coordinate \((u, v, 1)^T\) [34].

**2.2. Multitarget Information Interaction Network for Complex Traffic Scenes.** To predict the state of the target vehicle in complex traffic scenes, its future state is estimated according to its own running state and combined with the spatiotemporal interaction relationships with the surrounding environment. To effectively mine the interaction features in complex traffic data, the input data perceived by the onboard LiDAR should include vehicle size parameters and operation state parameters.

Figure 3 illustrates a multitarget information interaction network in a complex traffic scene. The intelligent vehicle equipped with a LiDAR sensor is located in the center of the road, and its operation state model is

\[
O^{(t)} = [L, W, X^{(t)}, Y^{(t)}, V^{(t)}, (X^{(t-5)}, Y^{(t-5)}, V^{(t-5)}) \cdots (X^{(t-1)}, Y^{(t-1)}, V^{(t-1)})],
\]

where \(L\) is the length of the intelligent vehicle, \(W\) is the width of the intelligent vehicle, and \(X^{(t)}, Y^{(t)}\) are, respectively, the horizontal and vertical axes coordinates of the center point of the onboard LiDAR. Moreover, \(V^{(t)}\) is the instantaneous velocity of the intelligent vehicle, and \((X^{(t-5)}, Y^{(t-5)}, V^{(t-5)}) \cdots (X^{(t-1)}, Y^{(t-1)}, V^{(t-1)})\) are the operation history status data of the intelligent vehicle.

The green vehicle in the front position perceived by the onboard LiDAR of the intelligent vehicle is \(O_1\), and the blue vehicle in the front-right position is \(O_2\). Moreover, the yellow vehicle in the front-left position is \(O_3\), and the red vehicle in the rear-right position is \(O_4\). \(O_1, O_2, O_3, \) and \(O_4\) are surrounding vehicles whose state behavior must be predicted. The green vehicle \(O_1\) is an example of the target, and its operation state model is

\[
O_1^{(t)} = [L_1, W_1, X_1^{(t)}, Y_1^{(t)}, V_1^{(t)}, (X_1^{(t-5)}, Y_1^{(t-5)}, V_1^{(t-5)}) \cdots (X_1^{(t-1)}, Y_1^{(t-1)}, V_1^{(t-1)})],
\]

where \(L_1\) is the target vehicle length, \(W_1\) is the target vehicle width, \(X_1^{(t)}\) and \(Y_1^{(t)}\) are, respectively, the horizontal and vertical axes coordinates of the center point of the target vehicle, \(V_1^{(t)}\) is the instantaneous velocity of the target vehicle, and \((X_1^{(t-5)}, Y_1^{(t-5)}, V_1^{(t-5)}) \cdots (X_1^{(t-1)}, Y_1^{(t-1)}, V_1^{(t-1)})\) are the operation history status data of the target vehicle.

The multtarget information interaction network model of the complex traffic scene presented in Figure 3 is as follows:

\[
C^{(t)} = [O^{(t)}, O_1^{(t)}, O_2^{(t)}, O_3^{(t)}, O_4^{(t)}],
\]
where $O^{(i)}$ is the operation state model of the intelligent vehicle and $O^{(2)}, O^{(3)}, O^{(4)}$, and $O^{(5)}$ are the operation state models of the front green vehicle, the front-right blue vehicle, the front-left yellow vehicle, and the rear-right red vehicle, respectively [34].

3. Vehicle Operational Risk Prediction Model Integrating Multiview and Interaction Information

3.1. Model Framework. The overall network architecture of the proposed vehicle motion state prediction model that integrates multiview point cloud features and multitarget interaction information is shown in Figure 4. The overall network architecture is mainly composed of a multiview point cloud feature extraction network, a multitarget interaction information extraction network, an Attention-BiLSTM prediction network, and an operational risk assessment network. The operational risk of multiple targets in the future is predicted by inputting the historical motion state information of the targets in the complex traffic scene obtained by the LiDAR sensors and the corresponding time sequences of the aerial view and front-view depth map point clouds.

3.2. Multiview Point Cloud Feature Extraction Network. Two improved VGG19 network models are used to extract multiview point cloud features. One branch extracts the point cloud top aerial view features, and the other branch extracts the point cloud front depth view features. The improved VGG19 network model adds several convolution layers on the basis of a shallow convolutional neural network (CNN). Because the addition of a convolution layer is more conducive to image feature extraction than the addition of a fully connected (FC) layer [35], the improved VGG19 network model can more easily overcome the diversity and complexity of traffic scenes than a shallow CNN and can ultimately achieve a better spatiotemporal feature extraction effect. As shown in the multiview point cloud feature extraction network in Figure 4, the VGG19 model has 16 convolution layers in total, among which the largest pooling layer is behind the convolution layer of layers 2, 4, 8, 12, and 16. The convolution kernel size in the convolution layer ranges from 224 × 224 reduced by half to 14 × 14. In this way, the use of a progressively decreasing convolution kernel is equivalent to the addition of implicit regularization, which can improve the feature extraction ability of the network and increase its operation speed.

Figures 5 and 6 show the process of the improved VGG19 network extracting feature map of point cloud top...
3.3. Multitarget Interaction Information Extraction Network. The data of the CNN input layer are convoluted and pooled layer by layer via the established multiple filters to extract the potential topological features between the data. The deeper the network, the more abstract the extracted features, and the better the robustness of the obtained features. The convolution in the convolution layer checks the data features output from the upper layer for the convolution operation and uses the activation function to construct the feature vector output. The corresponding mathematical model has been provided in a previous publication [36]. The multitarget interaction relationship corresponds to a one-dimensional (1D) time series, so a 1D CNN (1DCNN) can be used to extract the potential interaction relationship. Specifically, the corresponding local information can be calculated by sliding the convolution kernel of a specific size through the local area of the input data. A one-dimensional convolution has only one spatial dimension, and its convolution process is as follows:

$$X^{l+1}_{t,c} = \sum_{i=1}^{C_{in}} \sum_{k=1}^{K} W^l_{k,i,c} X^l_{t-1+k,i} + B_c, \quad (8)$$

where $X_t$ is the matrix corresponding to the input data, $C_{in}$ is equal to the number of input channels, $X^{l+1}_{t,c}$ is the $t$th parameter in the $c$th channel of layer $l + 1$, $W^l_{k,i,c}$ is the $k$th weight coefficient corresponding to the $i$th channel of the $c$th convolution kernel, $B_c$ is the offset coefficient of the corresponding convolution kernel, $k$ is the size of the convolution kernel, and $c$ is the step size of the convolution kernel.

As shown in the multitarget interaction information extraction network in Figure 4, the LiDAR information is input to obtain the multitarget historical motion state data of the time-sequence frame of the complex traffic scene. The potential spatiotemporal interaction diagram of the corresponding time-sequence frame extracted is output through the 1DCNN network, and each dynamic target is represented as a node. The nodes corresponding to any two targets in the same point cloud frame are connected with a solid line to represent the space edge, and the same target in adjacent frames is connected with a dotted line to represent the time edge.

3.4. Attention-BiLSTM Prediction Network. The output features of the multiview point cloud feature extraction network and the multitarget interaction information extraction network are fused, and the input model structure is presented in the Attention-BiLSTM prediction network shown in Figure 4. The model consists of an input layer, a BiLSTM layer, an attention layer, and an output layer. The input layer is the feature vector of the fused multiview point cloud features and multitarget interaction information. The attention mechanism can give different weights to the point cloud multiview and multitarget interaction characteristics of the input prediction network so as to highlight the influence of strong correlation factors and reduce the influence of weak correlation factors. The BiLSTM layer is composed of forward and backward LSTM layers. The mathematical model of the LSTM structural unit is given by
\begin{align}
    f_t &= \sigma_f(W_f(h_{t-1}, x_t) + b_f) \\
    i_t &= \sigma_i(W_i(h_{t-1}, x_t) + b_i) \\
    C_t &= \tanh(W_c(h_{t-1}, x_t) + b_c) \\
    o_t &= \sigma_o(W_o(h_{t-1}, x_t) + b_o) \\
    h_t &= o_t \tanh(C_t)
\end{align}

where \( x_t \) is the input data at time \( t \), \( h_{t-1} \) is the hidden layer output at time \( t - 1 \), \( \sigma_f \), \( \sigma_i \), and \( \sigma_o \) are the sigmoid functions of the forget gate, input gate, and output gate, respectively, \( f_t \), \( o_t \), and \( h_t \) are the final outputs of the forget gate, output gate, and current time unit, respectively, and \( i_t \), \( C_t \), and \( C_t \) are, respectively, the input gate, the tanh function, and the updated value of the unit state at the current time. Moreover, \( W_f \), \( W_i \), \( W_c \), and \( W_o \) are the weight matrices, and \( b_f \), \( b_i \), \( b_c \), and \( b_o \) are the offset terms [37].

During information processing via the BiLSTM model, the network layer status update of the BiLSTM model from front to back is given by

\begin{equation}
\overrightarrow{h_t} = H(W_{x\rightarrow h} x_t, W_{h\rightarrow h} \overrightarrow{h_{t-1}} + b_{h\rightarrow h})
\end{equation}

where \( H \) is the output function of the backward LSTM layer, \( W_{x\rightarrow h} \) is the weight matrix from the input layer to the forward LSTM layer, \( W_{h\rightarrow h} \) is the weight matrix between forward LSTM layers, and \( b_{h\rightarrow h} \) is the offset term.
The network layer status update of the BiLSTM model from back to front is given by

\[ \tilde{h}_t = H'(W_{xh} x_t + W_{hh} \tilde{h}_{t-1} + b_h), \]

where \( H' \) is the output function of the forward LSTM layer, \( W_{xh} \) is the weight matrix from the input layer to the backward LSTM layer, \( W_{hh} \) is the weight matrix between backward LSTM layers, and \( b_h \) is the offset term.

After the network layer is superimposed, the output of the unit cells of the BiLSTM model is

\[ h_t' = \tilde{H}(\tilde{h}_t, h_{t-1}, + W \tilde{h}_t + b_o), \]

where \( \tilde{H} \) is the output function of the output layer, \( W \) is the weight matrix from the forward LSTM layer to the output layer, \( W_{ho} \) is the weight matrix from the backward LSTM layer to the output layer, and \( b_o \) is the offset term.

The attention layer is the output of the learning function \( F \) added on the basis of the BiLSTM layer, as given by

\[ \xi_t = F(h_t'), \]

The weight coefficient \( \omega_t \) of the BiLSTM output vector \( h_t' \) is calculated by

\[ \omega_t = \frac{\exp(\xi_t)}{\sum_{t=1}^{n} \exp(\xi_t)}. \]

The linear weighting method is used to obtain the focus feature vector \( \alpha \), as given by the following equation, and the vehicle state prediction result is finally output.

\[ \alpha = \sum_{t=1}^{n} \omega_t h_t'. \]

3.5. Operational Risk Assessment Network. To quickly quantify the driving risk level of vehicles in the environment, the driving risk fields of obstacles are established. The driving risk fields comprehensively consider the overall size of obstacles and the relative movement between the obstacles and the intelligent vehicle. The vehicle operational risk field is the sum of the static and dynamic risk fields and is defined as follows [38]:

\[ U = U_{sta} + U_{dyn}, \]

where \( U \) is the operational risk field, \( U_{sta} \) is the static risk field, and \( U_{dyn} \) is the dynamic risk field.

The static risk field is only determined by the properties and shape of the obstacle, and its field strength is affected by two factors, namely, the relative distance between the intelligent vehicle and the obstacle and the direction of the intelligent vehicle approaching the obstacle. The smaller the relative distance between the intelligent vehicle and the obstacle, the greater the possibility of a traffic accident; thus, the strength of the static risk field is greater. The driving direction of motor vehicles is limited; that is, the lateral speed of a motor vehicle is usually much less than the longitudinal speed. Therefore, in the longitudinal direction of the obstacle, the static risk field has a large influence range, and the influence range in the lateral direction of the obstacle is small. Thus, a two-dimensional Gaussian function can be used for the static risk field of obstacles. Furthermore, considering the large overall size of the motor vehicle and the large field strength difference between the edge and the center point of the motor vehicle, it is inappropriate to use the two-dimensional Gaussian function of the first-order center distance. Therefore, the two-dimensional Gaussian function of the high-order center distance is used as the risk field of obstacles. The high-order center distance flattens the peak of the function so that the entire obstacle surface has a similar risk field strength. The static risk field is defined as

\[ U_{sta} = A \times \exp\left(\frac{(x-x_{obs})^2}{\sigma_x^2} + \frac{(y-y_{obs})^2}{\sigma_y^2}\right) \]

\[ \sigma_x = k_x \times L_{obs} \]

\[ \sigma_y = k_y \times W_{obs} \]

where \((x, y)\) are, respectively, the horizontal and vertical coordinates of a point in the traffic environment, \((x_{obs}, y_{obs})\) are, respectively, the abscissa and ordinate of the center point of the obstacle, \(A\) is the field strength coefficient, \(\beta\) is the high-order coefficient, \(\sigma_x\) and \(\sigma_y\) are the shape functions of the obstacle, \(L_{obs}\) is the length of the obstacle in the longitudinal direction, \(W_{obs}\) is the length of the obstacle in the lateral direction, and \(k_x\) and \(k_y\) are, respectively, the transverse- and longitudinal-dimension coefficients of the obstacle.

The dynamic risk field is determined by the movement of obstacles and intelligent vehicles. Thus, for the construction of the dynamic risk field, the movement of obstacles and intelligent vehicles must be comprehensively considered. The field strength of the dynamic risk field is mainly affected by four factors, namely, the relative distance, the absolute value of the relative speed, the direction of the relative speed, and the approach direction of the intelligent vehicle. When the relative speed direction and approach direction are the same, the smaller the relative distance and the greater the absolute value of the relative speed, the greater the possibility of a traffic accident, and the greater the field strength of the dynamic risk field. When the values of the other three items are the same, the greater the absolute value of the relative speed, the greater the possibility of a traffic accident, and the greater the field strength of the dynamic risk field. To meet the requirements, a dynamic risk field is established based on the two-dimensional Gaussian function. The formula of the dynamic risk field is
where $\sigma_v$ is the function of the speeds of the obstacle and intelligent vehicle, $v_{obs}$ is the speed of the obstacle in the longitudinal direction, $v$ is the longitudinal speed of the intelligent vehicle, $k_v$ is the velocity coefficient, rel. is a function describing the direction of relative motion between the obstacle and the intelligent vehicle, $\alpha$ is the relative velocity coefficient, and the definitions of the other parameters are the same as those for the static risk field.

4. Experiments and Result Analysis

To verify the effectiveness of the proposed vehicle motion state prediction method that integrates multiview point cloud features and multitarget interaction information, an intelligent vehicle experimental platform was employed for data collection. The experimental platform vehicle was a Shanghai Volkswagen Langyi 2013 1.6-L automatic comfort version; the dimensions of which were 4605 × 1765 × 1460 mm (length × width × height). The platform included RS-LiDAR-16 LiDAR, RS-LiDAR-32 LiDAR, a Gigabit Ethernet switch, an algorithm processor, a notebook computer, an uninterrupted power supply, and other equipment. The 16-line LiDAR could scan the surrounding environment with a vertical field of view (FOV) of between −15° and 15° and a horizontal FOV of 360°, a maximum ranging range of 150 m, and an output of $32 \times 10^4$ points per second with the scanning frequency set to 20 Hz. The 32-wire LiDAR can scan the surrounding environment with a vertical FOV of between −25° and 15° and a horizontal FOV of 360°, a maximum ranging range of 200 m, and an output of $60 \times 10^4$ points per second with the scanning frequency set to 20 Hz. The laptop was equipped with an Ubuntu 16.04 operating system, a CUDA 9.0 deep learning parallel computing acceleration kit, an NVIDIA GeForce GTX 1650 independent graphics card, and an Intel Core i5-9300H CPU with 2.4 GHz and 16 GB memory. The algorithm processor included built-in efficient environment detection-related algorithms. The Gigabit Ethernet switch ensured the high-speed data transmission of the data acquisition platform, and the uninterrupted power supply provided a reliable power supply for the experimental data acquisition equipment. The environmental point cloud data collected by LiDAR were sent to the Gigabit Ethernet switch through an Ethernet cable and transmitted to the algorithm processor for environmental information detection. The results were then sent to the notebook computer via Ethernet for storage and secondary operation processing visualization.

The test route and road information collection scene are shown in Figure 7. The test route was a two-way, four-lane urban road section on the East Second Ring Road in Guilin, Guangxi, with a total length of 4.2 km, of which 3.6 km is straight and 0.6 km is curved, and the speed limit on which is 60 km/h. During the test, the tester drove from the starting point, namely, the Liuhe intersection, to the end point (destination), namely, the Nanzhou Bridge, for about 7 min. To fully collect the point cloud data of the scene and the vehicle interaction information of the road section, the tester drove the intelligent vehicle experimental platform 40 times to collect data from different target vehicles, and focus was placed on extracting the scene data during multivehicle interaction for analysis. The intelligent vehicle experimental platform was divided into different target vehicle following data acquisition scenes 40 times, and different types of following scenes were divided. Moreover, 100 groups of following data were used as the training set, and 30 groups of following data were used as the test set.

To verify the prediction effect of the proposed Attention-BiLSTM model, the model was implemented on the Keras deep learning platform based on TensorFlow and was, respectively, compared with the FC, LSTM, and BiLSTM models on the same data set. The effects of the FC, LSTM, BiLSTM, and Attention-BiLSTM models on the global position $X$, global position $Y$, and relative speed $V$ are, respectively, presented in Figures 8(a)–8(c). As presented in the graphs, the red dotted line representing the prediction values of the proposed Attention-BiLSTM model was found to have the best fit with the blue solid line representing the real values. Therefore, the prediction effect of the Attention-BiLSTM model on the state of the target vehicle was better than those of the FC, LSTM, and BiLSTM models.

To further investigate the prediction effect of the proposed Attention-BiLSTM model on the global position $X$, global position $Y$, relative speed $V$, and other state parameters of the target vehicle in the multivehicle interaction scene of the multiview point cloud, a comparative experiment was designed, and the results are presented in Figure 9. The fitting degree of the true values (blue solid line) and the values predicted based on multiview point cloud features and vehicle interaction information (red dotted line) was found to be higher than that of the true values (blue solid line) and the values predicted based only on vehicle interaction information (yellow dotted line).

The mean square error (MSE) was used as the evaluation index to effectively evaluate the effect of the prediction model of the target vehicle state. Based on the statistics of the difference between the predicted and true values, the calculation formula is given as follows:

$$
\sigma_{MSE} = \frac{1}{n} \sum_{i=1}^{n} (P - R)^2,
$$

where $P$ is the predicted value and $R$ is the true value. A smaller value of the index $\sigma_{MSE}$ means that the predicted value is closer to the true value, which indicates that the
model has better performance and stronger feature expression ability.

As reported in Table 1, after 500 iterations of each model in the same multivehicle interaction scene, the MSE values of the prediction of the state parameters were ultimately obtained. It is evident that the MSE loss value of the proposed Attention-BiLSTM model was the lowest, and the prediction effect of this model on the motion state of the target vehicle was obviously better than those of the other models. Thus, the effect of target vehicle state prediction
based on multiview point cloud features and vehicle interaction information was found to be the best.

To further study the proposed Attention-BiLSTM model based on multiview point cloud features and vehicle interaction information for the analysis of the operational risk field of target vehicles surrounding an intelligent vehicle in a traffic scene, a historical continuous scene of interaction between an intelligent vehicle and four surrounding target vehicles was analyzed, as shown in Figure 10. Moreover, the historical time-sequence data of the state of the target vehicle corresponding to the input Attention-BiLSTM model are reported in Table 2.

Table 2 reports the state prediction results of target vehicles ID1, ID2, ID3, and ID4 surrounding an intelligent vehicle in a traffic scene in the next 3 s based on the proposed Attention-BiLSTM model.

To verify the prediction effect of the proposed Attention-BiLSTM model on the operational risk field of target vehicles ID1, ID2, ID3, and ID4 surrounding the intelligent vehicle in the traffic scene, the data in Table 3 were input into the operational risk assessment network.

Figure 11 presents the changes of the static risk fields of target vehicles ID1, ID2, ID3, and ID4 surrounding the intelligent vehicle in the traffic scene as predicted by the proposed Attention-BiLSTM model. Figures 11(a)–11(c) present the predicted changes of the strength of the static risk field of the target vehicle in the next 3 s. The strength of the static risk field was found to increase with the decrease of the relative distance between interactive vehicles. For the points close to the edge of the target vehicle, the field strength approached the peak value, and the field strength of the entire surface of the target vehicle was similar.

Figure 11(d)–11(f) present the predicted changes of the equipotential line of the static risk field of the target vehicle in the next 3 s. The equipotential line of the static risk field was found to have a large influence range in the longitudinal direction of the target vehicle. Moreover, affected by the edge length \( L \) and width \( W \) of the target vehicle detected by the LiDAR, the larger the vehicle size, the larger the range of the equipotential line of the risk field. Therefore, the static risk field established via the use of the high-order center distance two-dimensional Gaussian function meets the requirements.
strength was found to be less than the field strength relative velocity. The peak value of the dynamic risk field strength increased with the increase of the absolute value of vehicles. When the relative distance was equal, the field decreased of the relative distance between interactive risk field of the target vehicle in the next 3 s. The strength of the dynamic risk field was found to gradually increase with the decrease of the relative distance between interactive vehicles. When the relative distance was equal, the field strength increased with the increase of the absolute value of the relative velocity. The peak value of the dynamic risk field strength was found to be less than the field strength parameter, and it is related to the absolute value of the relative speed between the intelligent vehicle and the target vehicle; the greater the absolute value of the relative speed, the greater the peak value of the dynamic risk field strength. Figures 12(d)–12(f) present the predicted changes of the equipotential line of the dynamic risk field of the target vehicle in the next 3 s. The peak value of the equipotential line of the dynamic risk field was not at the edge of the vehicle, but was dynamically adjusted with the parameters, such as the relative speed and relative distance between the two vehicles and the size of the target vehicle. Therefore, the dynamic risk field established via the use of the high-order

Table 2: The historical time-series data of the target vehicle state input into the Attention-BiLSTM model.

|               | ID1 (L = 8.5 m, W = 3.0 m) | ID2 (L = 5.5 m, W = 2.4 m) | ID3 (L = 4.5 m, W = 2.0 m) | ID4 (L = 5.0 m, W = 2.2 m) |
|---------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| T = −4 s      | X (m) | Y (m) | V (m/s) | X (m) | Y (m) | V (m/s) | X (m) | Y (m) | V (m/s) | X (m) | Y (m) | V (m/s) |
| 6.85          | −14.95 | 6.8   | 3.36   | 12.0  | 8.20  | −9.67  | 2.5   | −15.57 | 13.66 | 7.4 |
| T = −3 s      | 7.14   | −15.29 | 6.8   | 3.85   | 1.59  | 12.1   | 9.13  | −10.65 | 2.8   | −15.26 | 13.27 | 7.5 |
| T = −2 s      | 7.03   | −15.34 | 6.8   | 4.06   | 1.36  | 11.8   | 8.48  | −9.94  | 2.3   | −15.23 | 13.02 | 7.4 |
| T = −1 s      | 7.28   | −15.62 | 7.1   | 4.26   | 1.16  | 11.6   | 8.35  | −10.02 | 1.8   | −15.03 | 12.90 | 7.6 |
| T = 0 s       | 7.32   | −15.68 | 6.9   | 4.45   | 0.90  | 11.5   | 8.54  | −10.15 | 1.4   | −14.96 | 12.64 | 8 |

Table 3: The state prediction effect of the Attention-BiLSTM model.

|               | ID1 | ID2 | ID3 | ID4 |
|---------------|-----|-----|-----|-----|
| T = 1 s       | X (m) | Y (m) | V (m/s) | X (m) | Y (m) | V (m/s) | X (m) | Y (m) | V (m/s) | X (m) | Y (m) | V (m/s) |
| 7.46          | −15.87 | 7.1   | 4.61   | 0.68  | 11.2  | 8.68   | −10.15 | 1.1   | −14.82 | 12.47 | 8 |
| T = 2 s       | 7.61   | −16.02 | 7.2   | 4.79   | 0.47  | 10.8   | 9.39  | −10.97 | 1.2   | −14.58 | 12.32 | 8.3 |
| T = 3 s       | 7.82   | −16.23 | 6.8   | 4.92   | 0.27  | 10.2   | 9.43  | −11.07 | 1.8   | −14.06 | 12.29 | 8.2 |

Figure 11: The changes of static risk field. (a) T = 1 s. (b) T = 2 s. (c) T = 3 s. (d) T = 1 s. (e) T = 2 s. (f) T = 3 s.

Figure 12 presents the changes of the dynamic risk field prediction of target vehicles ID1, ID2, ID3, and ID4 surrounding the intelligent vehicle in the traffic scene based on the proposed Attention-BiLSTM model. Figures 12(a)–12(c) present the predicted changes of the strength of the dynamic risk field of the target vehicle in the next 3 s. The strength of the dynamic risk field was found to gradually increase with the decrease of the relative distance between interactive vehicles. When the relative distance was equal, the field strength increased with the increase of the absolute value of the relative velocity. The peak value of the dynamic risk field strength was found to be less than the field strength parameter, and it is related to the absolute value of the relative speed between the intelligent vehicle and the target vehicle; the greater the absolute value of the relative speed, the greater the peak value of the dynamic risk field strength. Figures 12(d)–12(f) present the predicted changes of the equipotential line of the dynamic risk field of the target vehicle in the next 3 s. The peak value of the equipotential line of the dynamic risk field was not at the edge of the vehicle, but was dynamically adjusted with the parameters, such as the relative speed and relative distance between the two vehicles and the size of the target vehicle. Therefore, the dynamic risk field established via the use of the high-order
center distance two-dimensional Gaussian function meets the requirements.

Figure 13 presents the changes of the operational risk fields of target vehicles ID1, ID2, ID3, and ID4 surrounding the intelligent vehicle in the traffic scene predicted by the proposed Attention-BiLSTM model. Figures 13(a)–13(c) present the predicted changes of the strength of the operational risk field of the target vehicle in the next 3 s. The size of the operational risk field is related to the peak volume of the strength of the operational risk field. Figures 13(d)–13(f)
present the predicted changes of the equipotential line of the operational risk field of the target vehicle in the next 3 s. The red pentagram in the figure represents an intelligent vehicle, which is located at the geometric center of the operational risk field. The relative distance between target vehicle ID4 and the intelligent vehicle gradually increased, and the operational risk field of the vehicle was gradually weakened. Target vehicle ID2 and the intelligent vehicle were located in the same lane, their relative distance was small, and their relative speed was high. The operational risk field of the vehicle is the largest one by one. The relative speed between target vehicle ID3 and the intelligent vehicle was small, and the operational risk field of the vehicle was the smallest. The size of target vehicle ID1 was the largest, the relative distance from the intelligent vehicle gradually became closer, and the operational risk field of the vehicle was gradually enhanced. In summation, the constructed operational risk assessment network can effectively assess the operational risk of intelligent vehicles.

5. Conclusion

To effectively predict the operational risk between intelligent vehicles and surrounding traffic participants in complex scenes, a vehicle motion state prediction algorithm that integrates the multiview features of point cloud time series and multitarget interaction information was proposed. This proposal was based on the characteristics of object motion affected by the surrounding environment and the interaction of surrounding objects, as well as on the complex traffic environment perception technology of dual multilane LiDAR. Artificial potential field theory was applied to construct the operational risk assessment network. With the assistance of the real-time point cloud information perceived by the LiDAR, the time-sequence bird’s-eye view and range image are obtained, and the time-sequence high-level abstract combined features in the multiview scene are extracted by using the improved VGG19 network model. These features are then fused with the potential spatiotemporal interaction features obtained by extracting the multitarget operation state data detected by the LiDAR by using a 1DCNN. The temporal feature vector is constructed as the input data of the attention network, and the desired input-output mapping relationship is trained to predict the motion states of traffic participants. The results of experiments demonstrated that the prediction effect of some state parameters, including the global position X, global position Y, and relative speed V of the target vehicle, achieved by the proposed Attention-BiLSTM model was better than that achieved by the FC, LSTM, and BiLSTM models. Moreover, the prediction effect of the intelligent vehicle operational risk field based on multiview point cloud features and vehicle interaction information was found to be good. The results of this study can provide support for follow-up research on the recognition of the behavior intention of unmanned vehicles.

Data Availability

The data used to support the findings of this study have not been made available due to data privacy.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was jointly supported by the National Key R&D Program of China under Grant 2019YFB1600500, the Changjiang Scholars and Innovative Research Team in University under Grant IRT_17R85, the National Natural Science Foundation of China under Grants 51775053 and 51908054, the Natural Science Foundation of Guangxi Province under Grant 2020GXNSFAA159071, Guangxi University (the Young and Middle-Aged Teachers Basic Ability Enhancement Project) under Grants 2019KY0819 and 2020KY21014, and Guangxi Vocational Education Teaching Reform Research Project under Grant GXGZJG2019A035.

References

[1] X. Fan, B. Zhou, and H. H. Wang, “Urban landscape ecological design and stereo vision based on 3D mesh simplification algorithm and artificial intelligence,” Neural Processing Letters, vol. 53, pp. 1–17, 2021.
[2] T. Humphreys, M. J. Murrian, and L. Narula, “Deep-urban unaided precise global navigation satellite system vehicle positioning,” IEEE Intelligent Transportation Systems Magazine, vol. 12, no. 99, pp. XX1, 2020.
[3] M. Car, L. Markovic, A. Ivanovic, M. Orsag, and S. Bogdan, “Autonomous wind-turbine blade inspection using LiDAR-equipped unmanned aerial vehicle,” IEEE Access, vol. 8, no. 99, p. 1, 2020.
[4] Z. Zhang, X. Yang, D. Xu, K. Geng, Y. Meng, and G. Feng, “One way to fill all the concave region in grid-based map,” Robotics, vol. 39, pp. 1–17, 2020.
[5] J. Laconte, E. Randriamiarintsoa, A. Kasmi et al., “Dynamic Lambda-Field: A Counterpart of the Bayesian Occupancy Grid for Risk Assessment in Dynamic Environments,” 2021, https://arxiv.org/abs/2103.04795.
[6] F. Xu, H. Wang, B. Hu, and M. Ren, “Road boundaries detection based on modified occupancy grid map using millimeter-wave radar,” Mobile Networks and Applications, vol. 25, no. 4, pp. 1496–1503, 2020.
[7] O. Erkent, C. Wolf, and C. Laugier, “End-to-End learning of semantic grid estimation deep neural network with occupancy grids,” Unmanned Systems, vol. 7, no. 3, pp. 171–181, 2019.
[8] M. Lee, S. Kim, W. Lim, and M. Sunwoo, “Probabilistic occupancy filter for parking slot marker detection in an autonomous parking system using AVM,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 6, pp. 2389–2394, 2019.
[9] M. M. Rana, R. Bo, and A. Abdelhadi, “Distributed grid state estimation under cyber attacks using optimal filter and bayesian approach,” IEEE Systems Journal, vol. 15, no. 99, pp. 1–9, 2020.
[10] K. Lee and D. Kum, “Collision avoidance/mitigation system: motion planning of autonomous vehicle via predictive occupancy map,” IEEE Access, vol. 7, no. 99, pp. 52846–52857, 2019.
[11] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," The International Journal of Robotics Research, vol. 5, no. 1, pp. 90–98, 1986.

[12] L. Li, J. Gan, X. Qu, W. Lu, P. Mao, and B. Ran, "A dynamic control method for cavs platoon based on the MPC framework and safety potential field model," KSCE Journal of Civil Engineering, vol. 25, no. 2, 2021.

[13] H. Heidari and M. Saska, "Collision-free trajectory planning of multi-rotor UAVs in a wind condition based on modified potential field," Mechanism and Machine Theory, vol. 156, no. 1, Article ID 104140, 2021.

[14] H. Sang, Y. You, X. Sun, Y. Zhou, and F. Liu, "The hybrid path planning algorithm based on improved A* and artificial potential field for unmanned surface vehicle formations," Ocean Engineering, vol. 223, no. 3–4, Article ID 108709, 2021.

[15] J.-B. Receveur, S. Victor, and P. Melchior, "Autonomous car decision making and trajectory tracking based on genetic algorithms and fractional potential fields," Intelligent Service Robotics, vol. 13, no. 2, pp. 315–330, 2020.

[16] K. Gao, D. Yan, F. Yang et al., "Conditional artificial potential field-based autonomous vehicle safety control with interference of lane changing in mixed traffic scenario," Sensors, vol. 19, no. 19, p. 4199, 2019.

[17] K. S. Essa and E. R. Abo-Ezz, "Potential field data interpretation to detect the parameters of buried geometries by applying a nonlinear least-squares approach," Acta Geodaetica et Geophysica, vol. 56, no. 2, pp. 387–406, 2021.

[18] T. Hesse and T. Sattel, "An approach to integrate vehicle dynamics in motion planning for advanced driver assistance systems," in Proceedings of the Intelligent Vehicles Symposium, Istanbul, Turkey, June 2007.

[19] S. Cheng, L. Li, H.-Q. Guo, Z.-G. Chen, and P. Song, "Longitudinal collision avoidance and lateral stability adaptive control system based on MPC of autonomous vehicles," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 99, pp. 1–10, 2019.

[20] Z. Tang, B. Chen, R. Lan, and S. Li, "Vector field guided RRT* based on motion primitives for quadrotor kinodynamic planning," Journal of Intelligent and Robotic Systems, vol. 100, no. 6, 2020.

[21] C. Parzani and F. Filbet, "On a three dimensional vision based collision avoidance model," Journal of Statistical Physics, vol. 168, no. 3, pp. 680–706, 2017.

[22] X. Song, D. Jones, N. Asgari, and T. Pigden, "Multi-objective vehicle routing and loading with time window constraints: a real-life application," Annals of Operations Research, 2019.

[23] T. Choe, J.-B. Park, S. Joo, and Y. Park, "1d virtual force field algorithm for reflexive local path planning of mobile robots," Electronics Letters, vol. 50, no. 20, pp. 1429-1430, 2014.

[24] S. J. Subramanian and N. Nigam, "On a boundary condition used in Virtual Fields methods," Mechanics Research Communications, vol. 63, pp. 41–47, 2015.

[25] J. M. Considine, F. Pierron, K. T. Turner, and D. W. Vahey, "General anisotropy identification of paperboard with virtual fields method," Experimental Mechanics, vol. 54, no. 8, pp. 1395–1410, 2014.

[26] C. Sun, G. Hu, L. Xie, and M. Egerstedt, "Robust finite-time connectivity preserving coordination of second-order multi-agent systems," Automatica, vol. 89, pp. 21–27, 2018.

[27] J. Bi, Y. Zhou, Z. Tang, and Q. Luo, "Artificial Electric Field Algorithm with Inertia and Repulsion for Spherical Minimum Spanning Tree," Applied Intelligence, vol. 52, pp. 1–20, 2021.

[28] S. Islam and N. I. Xiros, "Robust asymptotic and finite-time tracking for second-order nonlinear multi-agent autonomous systems," International Journal of Control, Automation, and Systems, vol. 17, pp. 1–10, 2019.

[29] J. Huang, H. Fang, J. Chen, L. Dou, and F. Deng, "Cooperative adaptive fuzzy control of high-order nonlinear multi-agent systems with unknown dynamics," IFAC Proceedings Volumes, vol. 47, no. 3, pp. 9774–9779, 2014.

[30] Y. Luo and W. Zhu, "Event-triggered H-infinity finite-time consensus control for nonlinear second-order multi-agent systems with disturbances," Advances in Difference Equations, vol. 2021, no. 1, pp. 1–19, 2021.

[31] A. Thierbach, D. Schmidtel, and A. Görling, "Robust and accurate hybrid random-phase-approximation methods," The Journal of Chemical Physics, vol. 151, no. 14, Article ID 144117, 2019.

[32] M. Ahmad, E. Al-Solami, A. M. Alghamdi, and M. A. Yousa, "Bijective S-Boxes Method Using Improved Chaotic Map Based Heuristic Search and Algebraic Group Structures," IEEE Access, vol. 8, no. 99, p. 1, 2020.

[33] I. Kamon, E. Rimon, and E. Rivlin, "TangentBug: a range-sensor-based navigation algorithm," The International Journal of Robotics Research, vol. 17, no. 9, pp. 934–953, 1998.

[34] R. Zhang, Y. Guo, Y. Long, Y. Zhou, and C. Jiang, "Vehicle motion state prediction method integrating point cloud time series multiview features and multitarget interactive information," Journal of Advanced Transportation, vol. 2022, Article ID 4736623, 21 pages, 2022.

[35] S. Guan, M. Lei, and H. Lu, "A Steel Surface Defect Recognition Algorithm Based on Improved Deep Learning Network Model Using Feature Visualization and Quality Evaluation," IEEE Access, vol. 8, no. 99, p. 1, 2020.

[36] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

[37] L. Luo, Z. Yang, P. Yang et al., "An attention-based BiLSTM-CRF approach to document-level chemical named entity recognition," Bioinformatics, vol. 34, no. 8, p. 8, 2017.

[38] A. Ardeshiri, M. Jihani, and S. Peeta, "Driving simulator-based study of compliance behavior with dynamic message sign route guidance," IET Intelligent Transport Systems, vol. 9, no. 7, pp. 765–772, 2015.