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Comparison of the Pedestrian Crossing Intention Parameters and Research on Intention Recognition Model Under Different Road Conditions

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ABSTRACT There have a large number of pedestrian-vehicle accidents on the pedestrian crossing area in China every year, causing huge loss of life and property. In view of different road conditions, it's crucial to establish a more accurate crossing intention recognition model to improve the safety of pedestrians. In this work, a pedestrian crossing area was chosen. Due to construction reasons, two road conditions appeared in the same crossing area at different periods, namely a condition with a zebra crossing and that without a zebra crossing. We compared pedestrian crossing intention parameters under two road conditions in the same crossing area. The results found that there was a great difference in the characterization parameters of pedestrian crossing intention when the site with and without a zebra crossing. Additionally, a more comprehensive crossing intention characteristic parameters set was established. The characteristic parameters were pedestrian speed, the distance between vehicle and crossing area, time to collision (TTC), and safe vehicle deceleration (SVD), pedestrian age, pedestrian gender, group, respectively. The pedestrian intention recognition model for the site with a and without a zebra crossing were established by long short-term memory network integrated with the attention mechanism (AT-LSTM). When the model recognized pedestrian crossing intention 0.6 seconds in advance, the recognition accuracies were 93.05% and 93.89% respectively. The research results are of great significance for improving the safety of autonomous vehicles in the future, and there are also important to improve pedestrian safety.

INDEX TERMS Natural observation data, intention recognition, autonomous vehicles, intention parameter set, attention mechanism.

I. INTRODUCTION

In recent years, with the rapid development of China's economy and the continuous improvement of its urbanization level, its urban skeleton has continued to expand and its road networks have continued to extend; simultaneously, residents' consumption ability has been constantly enhanced, and the number of motor vehicles continues to increase rapidly. However, the construction of supporting facilities related to road traffic is relatively lagging, residents' awareness and experience of traffic safety are relatively insufficient, and the conflict between pedestrians and vehicles on the zebra crossing is becoming more and more serious. Even in cities, there are many zebra crossings without traffic signal control, and traffic accidents caused by pedestrians at these zebra crossings are common [1].

As a vulnerable group of traffic participants, pedestrians are the most susceptible to injury. According to the annual report on road traffic accident statistics released by the Traffic Administration Bureau of the Ministry of Public Security in 2017, the number of pedestrian walking injuries in traffic accidents accounted for 16.72% of all traffic-related injuries, and the number of injured pedestrians was 35,058. The death toll accounted for 27.11% of all traffic-related deaths, with a total of 17,286 deceased pedestrians [2].

At present, the main causes of pedestrian-vehicle accidents are as follows: The driver has insufficient perception of the surrounding environment and cannot accurately

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judge the pedestrians' crossing intention, resulting in a pedestrian-vehicle collision [3],[4]. The vehicles are not yield according to regulations and pedestrians cross illegally [5].

Intelligent autonomous vehicles are a future development trend, and their related technology has also been rapidly developed in recent years; both domestic and foreign large-scale technology companies (Google, Uber, etc.) and vehicle enterprises (Tesla, BMW, etc.) have carried out related tests. In the future, the key to whether intelligent autonomous vehicles can significantly reduce traffic accidents between pedestrians and vehicles as compared with manual driving is whether they can effectively identify a pedestrian's intention to cross the street. Because the perception range of intelligent autonomous vehicles to view the surrounding environment is wider and more detailed, it can, to a certain extent, prevent traffic accidents caused by the driver's insufficient perception of the surrounding environment [6].

In March 2018, an Uber automated vehicle was involved in a fatal accident. The main reason for the accident was that the pedestrian has been found by the automatic driving vehicle 5.6 s before the impact, but the pedestrian's intention has not been correctly identified. If automated vehicles can accurately identify the intentions of pedestrians to cross the street and then engage in emergency braking, the accidents may be avoided [7].

How to reduce the risk of pedestrian-vehicle conflicts, establish an effective pedestrian crossing safety assessment and early warning mechanism, and comprehensively improve the pedestrian crossing safety level are particularly important research directions. Additionally, if a vehicle can accurately judge that there a pedestrian has no intention to cross, it can drive at the original speed, thereby improving driving comfort and efficiency. At present, both domestic and foreign scholars have conducted substantial research on pedestrian crossing behavior and pedestrians' intentions at intersections and zebra crossings [8].

II. RELATED WORK

The premise of the accurate identification of pedestrian crossing intention is the comprehensive and appropriate selection of representative parameters of intention. At present, the research on street crossing intention can be mainly categorized into two aspects: machine learning intention recognition methods based on big data-driven, and intention recognition methods based on mathematical models; in this work, only the first type of method is discussed. Based on the prediction of pedestrian trajectory, Quintero Mínguez *et al.* [9], Quintero *et al.* [10], [11] identified the pedestrian's intention to cross the street by integrating characteristics such as pedestrian posture; although the identification accuracy was high, the identification time lagged to a certain extent. Quintero Mínguez *et al.* [9] proposed an intention recognition model based on a dynamic Bayesian network based on changing pedestrian head and body postures. Völz *et al.* [13]–[15] analyzed and predicted pedestrian movement around urban roads in the context of future urban autonomous driving, and focused on the analysis and prediction of pedestrian movement near zebra crossings. Pedestrian intention recognition model based on a support vector machine (SVM) was established. However, in Volz's study, the parameter set of intention characterization was relatively small, which may have a certain influence on the accuracy of intention recognition. Variimidis *et al.* [16] studied a variety of feature extraction methods combined with a centralized machine learning algorithm to establish an automatic pedestrian movement detection system; the focus was placed on data on pedestrians' body and head movements, and it was then predicted whether the pedestrian had the intention to cross the road. Bandyopadhya *et al.* [17] considered pedestrians passing near traffic lights and established a hidden Markov intention recognition model that consists of three parts, namely spatial context recognition, hidden Markov-based learning, and intention recognition. Fang *et al.* [18], Fang and López [19] divided pedestrian crossing intentions into three types, namely starting, crossing, and stopping, and established a pedestrian crossing intent recognition model based on SVM; the recognition accuracy rate reached 93%. However, there was no further analysis of the advance recognition of intention in the study. Rasouli *et al.* [20], [21] analyzed the crossing parameters of a pedestrian and the surrounding environmental parameters of the pedestrian while crossing, determined the parameters that represent the pedestrian's intention to cross, and used a machine-learning algorithm to identify whether the pedestrian should cross the street.

Camara *et al.* [22] constructed a set of representative parameters of the pedestrian crossing, which mainly included the pedestrian crossing trajectory, the vehicle trajectory, and the relative position of any vehicle; on this basis, a pedestrian intention recognition model was established. The results demonstrated that the model had high recognition accuracy; however, the set of representative parameters was not sufficiently comprehensive, and advance recognition was not discussed. Zhao *et al.* [23] extracted the parameters of the trajectory of a pedestrian crossing at an intersection and established an improved naive Bayesian intention recognition model. The verification results revealed that the model had good recognition accuracy 0.5 s in advance. Hashimoto *et al.* [24], [25] established a recognition model for the intention of pedestrians to cross at intersections, and their validation results showed that the model can well express pedestrian crossing decisions. Schneemann and Heinemann [26] established an improved SVM intention recognition model based on pedestrian motion characteristics and pedestrian attitude parameters; however, the model did not consider the parameters of the surrounding environment and vehicle. Skovierová *et al.* [27] collected data on the parameters of the pedestrian position and speed, the number of pedestrians, and the direction of movement to identify pedestrian crossing intention. The results revealed that the model can well reflect pedestrian crossing decisions.

TABLE 1. Summarize of the previous crossing intention study.

Author	Variable	Study site	Performance	Time Horizon
Quintero [9]-[11]	Positions and displacements of 11 joints located along the body	With a zebra crossing	95.13%	0 s in advance
Huang [9]	Head pose	—	87.77%	—
Völz [13]-[15]	Distance between pedestrian and curb; distance between vehicle and zebra crossing;	With a zebra crossing	84.74%	—
Rasouli [20],[21]	age, gender, motion direction, head orientation	With a zebra crossing/ without a zebra crossing	80.23%	—
Fang [18]	Body posture	With a zebra crossing/ without a zebra crossing	86%	—
Zhao [23]	x, y, pedestrian speed, pedestrian direction	with a zebra crossing	92.60%	0.5s in advance
Hashimoto [24],[25]	Distance to crosswalk, pedestrians speed	With a zebra crossing	84% (standing); 93% (walking); 48% (running)	—
Skovierová [27]	Pedestrian distance to the zebra, pedestrian distance to the road, Angle between the pedestrian and the zebra	With a zebra crossing	85.60%	1 s in advance

We summarized the previous literature review and established Table 1. It can be seen from Table 1 that there are still some problems in the existing pedestrian intention research. a). The characterization parameters of crossing intention are not comprehensive enough. The recognition accuracy of crossing intention model is not high, especially in a certain time in advance. To solve these problems, this paper establishes comprehensive crossing intention set and a novel intention recognition model, that is, long short-term memory integrated with the attention mechanism (AT-LSTM) model. b). It can be seen from Table 1 that few scholars studied the pedestrians crossing intention at the site without a zebra crossing. In this work, the zebra crossing was removed from April 14 to May 17, and the zebra crossing was installed from May 18 to May 31. We compared and analyzed the pedestrian crossing intention under two types of zebra crossing in the same crossing area.

In view of these problems, a common zebra crossing without traffic signal control in Xi'an, China was selected for research in the present study. Due to road construction, this crossing area existed both with and without a zebra crossing at different times. In this paper, the differences in the representative parameters of pedestrian crossing intention in the presence and absence of a zebra crossing without traffic signal control are analyzed, and pedestrian crossing intention is identified. In addition, it is found that, in most cases, the standard for pedestrians to measure whether they are allowed to cross the street is whether an oncoming vehicle can safely brake within the distance from the current vehicle's position to the crossing area. Based on this, this paper proposes the use of safe vehicle deceleration (SVD) as an important representation parameter of the intention of a pedestrian to cross the street. To more accurately identify pedestrians' crossing intentions and provide information for intelligent vehicles, the parameters of the pedestrian speed, distance between pedestrian and crossing area, vehicle speed, the distance between vehicle and crossing area, time to collision (TTC), SVD, the age of pedestrians, the gender of pedestrians and group are also introduced.

III. METHOD

A. LONG SHORT-TERM MEMORY NETWORK (LSTM)

The LSTM was a special type of recurrent neural network (RNN), which can learn the data information of long time series. The LSTM was proposed by Hochreiter and Schmidu-ber [28] in 1997 and improved by Graves [29]. LSTM consists of input gate, output gate and memory gate. It is mainly used to maintain and control cell state. The specific description is as follows:

Input gate: Memorize some current information. The formula was shown in (1) and (2):

$$i_t = sigmoid(W_i \cdot [h_{t-1}, x_i]) \tag{1}$$
$$\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_i]) \tag{2}$$

where i_t is the input gate, $\tilde{C}_t$ is the input state value, h_{t-1} is the last output, x_i is the current input, and W_i is the input gate weight matrix.

Forget gate: Choose to forget some information in the past. The formula was shown in (3).

$$f_t = Sigmoid(W_f \, [h_{t-1}, x_t]) \tag{3}$$

where f_t is the forget gate, and W_f is the forget gate weight matrix.

Combine past and present memories. The formula was shown in (4).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{4}$$

where C_t is the new state.

Output gate. This process was shown in formula (5) and (6):

$$o_t = Sigmoid(W_o \cdot [h_{t-1}, x_t]) \tag{5}$$
$$h_t = o_t \cdot tanh(C_t) \tag{6}$$

where o_t is the output gate. h_t is the output value, and W_o is the weight matrix of output gate.

B. LONG SHORT-TERM MEMORY NETWORK MODEL WITH ATTENTION MECHANISM (AT-LSTM)

The attention mechanism is an efficient way to obtain information. On the one hand, it can actively query the most relevant information at each step, while ignoring the irrelevant information. On the other hand, it greatly shortens the distance of information flow and speeds up the speed of information processing. The recognition of pedestrian crossing intention is a temporal classification problem. In order to improve the recognition accuracy and recognition speed, attention mechanism and LSTM are fused in this paper. Fig. 1 is the frame diagram.

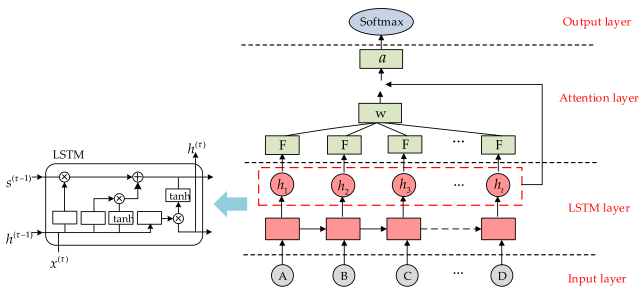


FIGURE 1. AT-LSTM framework.

The framework includes four layers: input layer, LSTM layer, Attention layer and output layer. The working process of LSTM layer has been described in detail in the previous section. The attention layer works as follows:

A learning function F is used to calculate the weight W_t of the output vector h_t of the LSTM layer, and the final feature representation vector a is obtained by weighting. Finally, the recognition result of the pedestrian crossing intention is transmitted through the softmax layer. The calculation formula is shown in (7):

$$e_t = F\left(h_t\right) \tag{7}$$

where h_t represents the output of the LSTM layer at time t. The calculation formula of weight W_t is shown in (8):

$$W_t = \frac{\exp(e_t)}{\sum_{i=1}^{n} \exp(e_i)} \tag{8}$$

The formula is then weighted to obtain feature representation vector a, and its formula is shown in (9):

$$a = \sum_{t=1}^{n} \exp(W_t h_t) \tag{9}$$

C. AT-LSTM MODEL INPUT AND PARAMETER SETTING

Pedestrian crossing intention recognition can be regarded as a time series modeling and prediction problem. In this paper, intention association features are extracted through the continuous data flow of time series before the pedestrian and vehicle cross the street, then AT-LSTM is adopted for classification of pedestrian crossing intention.

The time series of each characteristic parameter T-0 s is expressed as a characteristic vector. Assuming that the number of input parameters is n, the input format of the model is $\boldsymbol{M^T} = [\boldsymbol{X_1^T}, \boldsymbol{X_2^T}, \boldsymbol{X_3^T}, \ldots, \boldsymbol{X_n^T}]$, where $\boldsymbol{T}$ is the time series length of 0-T s. When the model is identified 0.6 s in advance, the input of the model is $\boldsymbol{M^n} = [\boldsymbol{X_1^u}, \boldsymbol{X_2^u}, \boldsymbol{X_3^u}, \ldots, \boldsymbol{X_n^u}]$, where $\boldsymbol{u}$ is the length of 0.6-T s time series.

In this work, the MATLAB language was used to developed the model. Through the grid search method, we determine the parameters of the model training. The AT-LSTM network is composed of four layers of the stack, the dropout rate is 0.4, the number of hidden units per layer is 128, and the max epochs is 80. Adam optimizer is adopted in the network, with a learning rate of 0.01. The activation function of a fully connected layer is ReLU,.

D. SUPPORT VECTOR MACHINE (SVM)

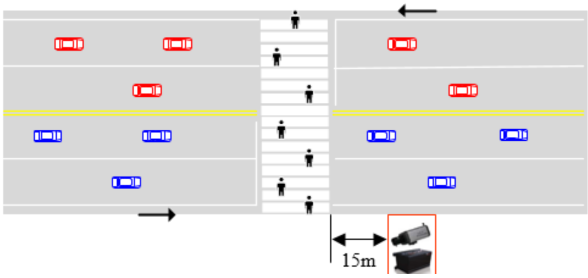
Support vector machine (SVM) is a widely used pattern recognition algorithm [30]. The SVM is a two-classification model. Its basic model is the linear classifier with the largest interval defined in the feature space. The largest interval makes it different from the perceptron machine. The learning strategy of SVM is to maximize the interval, which can be formalized as a problem of solving convex quadratic programming, which is also equivalent to the problem of minimizing the regularized hinge loss function. The learning algorithm of SVM is the optimal algorithm for solving convex quadratic programming.

The classification performance of SVM algorithm is closely related to kernel function, penalty parameter c and kernel function parameter g. In order to achieve better classification and recognition effect, the kernel function of SVM selects the radial basis function with better performance. The optimal values of penalty parameter c and kernel function parameter g are determined by grid search method. The values are 4 and 0.17 respectively.

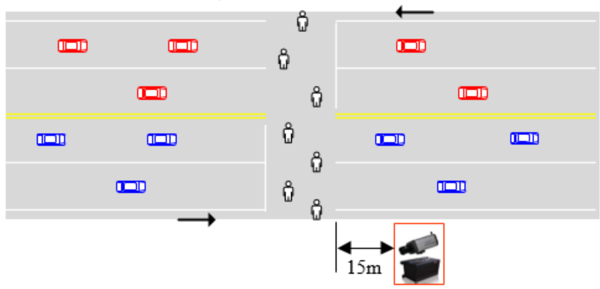
IV. EXPERIMENTAL

A. EXPERIMENTAL SITE

The crossing area selected in this paper is located in the southern section of Wenyi Road, which is a two-way, four-lane road, and the width of each lane is 3 m. There is no green belt, barrier, or refuge island in the middle of the road. The center of the road is separated by double yellow lines. The maximum speed limit of the selected road section is 60 km/h. The traffic flow is about 600 veh/h during rush hours and 400 veh/h during non-rush hours. The road elements are mainly composed of private cars, taxis, and buses. The selected crossing area without traffic control and the road type are common in Xi'an City, and are also common in China. There is no signal control at the selected crossing area, and no electronic police equipment is installed. Due to road construction, during the experiment, there were two states



(a). with a zebra crossing



(b) without a zebra crossing.

FIGURE 2. The road plane structure.

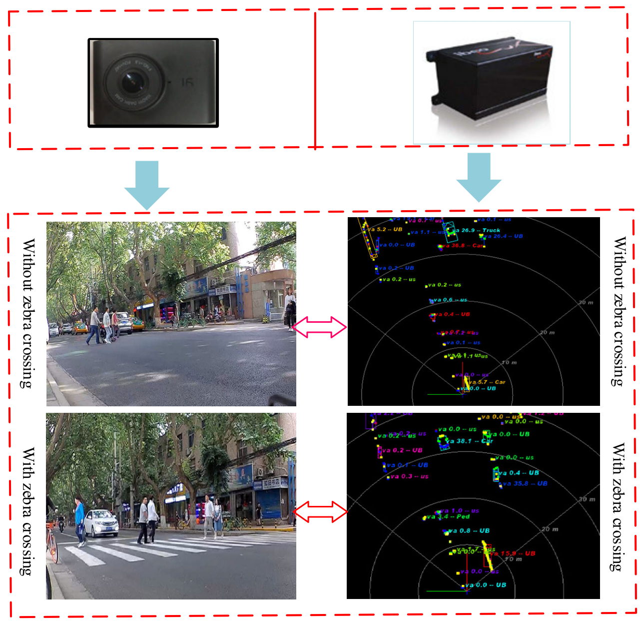


FIGURE 4. Parameter acquisition equipment.

of the road in the same place at different times, namely the presence and absence of a zebra crossing. The road plane structure and photos of the experimental site are respectively presented in Fig. 2 and Fig. 3.

(a). with a zebra crossing

(b) without a zebra crossing.

FIGURE 3. Photographs of the experimental site.

B. EXPERIMENTAL EQUIPMENT

For the research of pedestrian crossing decision-making, the main equipment used was four-layer lidar and a high-definition (HD) camera, as shown in Fig. 4. The lidar model was an IBEO LUX 4L-4 with a scanning frequency of 12.5 Hz, a detectable range of 0.3–200 m, a vertical viewing angle of 3.2°, and a horizontal viewing angle of 110°. The video resolution of the HD camera was 1920 × 1080.

The experimental equipment was placed on one side of the road, 0.6 m away from the ground, and 15 m away from the zebra crossing. After debugging, the equipment could completely cover the entire road. It should be noted that the purpose of using the video camera and four-layer lidar was to more accurately judge whether a pedestrian reached the curb. Judgment via only the use of lidar will create large errors in recognition time. Moreover, intention recognition is a continuous process; the intention representation data for a certain period of time is required to judge pedestrian intentions. If the recognition time is not fine enough, it is difficult to apply it to precise intelligent vehicles. It was also considered that the ‘‘observer effect’’ would affect the experiment; thus, to eliminate its influence, the equipment was placed in a concealed area as far from the road as possible. In addition, the data collected in this experiment were used only for the experiment.

C. DATA COLLECTION

All the data were collected in May 2018; because the impact of weather on pedestrian intention was not considered in this paper, only sunny weather was selected for the acquisition of pedestrian crossing data. The site without a zebra crossing from May 1 to May 17, and the site with a zebra crossing from May 18 to May 31. In order to obtain more crossing sample size, we choose the time when the number of pedestrians and vehicles is relatively large. The time for data collection were 7.30-9.00 in the morning and 5.30-7.00 in the evening; data were collected for nearly 3 hours every day. There are about 8 days of bad weather in May. Excluding these 8 days, about

67.5 hours of data in May were selected. The data includes about 35.5 hours without a zebra crossing and about 32 hours with a zebra crossing.

In this work, the pedestrian intention was categorized as crossing-crossing and crossing-waiting. Crossing-crossing means that the current traffic conditions allow pedestrians to pass safely without apparent stopovers. Crossing-waiting means that the current conditions cannot meet the safety of pedestrians crossing the street, and the pedestrians need to wait for a better opportunity to cross.

To conduct the more accurate modeling of pedestrian crossing intentions, it was also necessary to extract information about the surrounding vehicles and the movement information of the pedestrians themselves. The extracted data included the distance between the pedestrians and crossing area, the pedestrian speed, the vehicle speed, the distance between the vehicle and crossing area, the TTC, SVD, age, gender and group. The recognition of pedestrians' intentions to cross a street is a continuous process; therefore, to accurately judge the pedestrian's intention to cross a street, it is necessary to accurately select the data from a moment at which the pedestrian has not yet reached the crossing area to the moment at which the pedestrian has reached the crossing area. This is illustrated in Fig. 5.

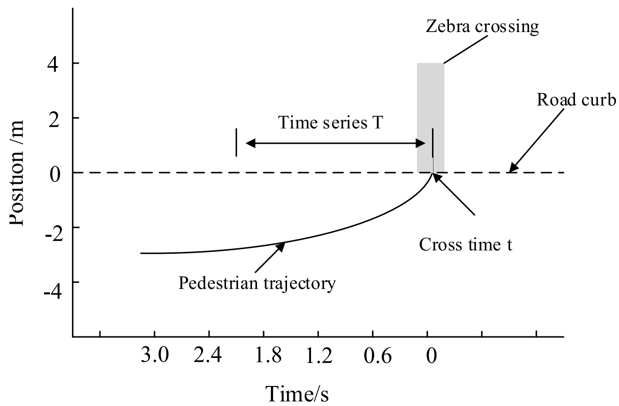


FIGURE 5. Time series of the pedestrian crossing area.

In total, 3600 effective samples were extracted, which included 1800 crossing-crossing samples composed of 900 samples with a zebra crossing and 900 samples without a zebra crossing. Moreover, there were 1800 crossing-waiting samples that also included 900 samples with a zebra crossing and 900 samples without a zebra crossing. The process of model recognition is therefore essentially a binary classification problem.

The detailed definitions of some parameters are provided as follows.

The distance between the pedestrian and the crossing area Dis_{ped} (m) refers to the arithmetic square root of the sum of the square of the longitudinal distance (dis_{lon}) between the pedestrian and curb and the square of the transverse distance (dis_{tran}).

$$Dis_{ped} = \sqrt{dis_{lon}^2 + dis_{tran}^2} \tag{10}$$

The distance between the vehicle and the crossing area Dis_{veh} (m) refers to the vertical distance between the current location of the vehicle and the location of the crossing area.

TTC (s) refers to the ratio of the distance between the vehicle and the crossing area to the vehicle speed.

$$TTC = \frac{Dis_{veh}}{S_{veh}} \tag{11}$$

SVD (m/s^2) refers to the deceleration speed at which a vehicle can safely stop before decelerating from its current position to the crossing area. In general, pedestrians judge their ability to cross a street safely by considering the ability of a vehicle traveling at its current speed to stop safely within a distance from the vehicle's current position to the crossing area. Therefore, in this work, SVD is first introduced to the identification of a pedestrian's intention to cross the street. The expression is the square of the initial speed (V_T) minus the square of the final speed (V_O) divided by twice the distance between the vehicle and the zebra crossing (Dis_{veh}).

$$SVD = \frac{V_T^2 - V_O^2}{2Dis_{veh}} \tag{12}$$

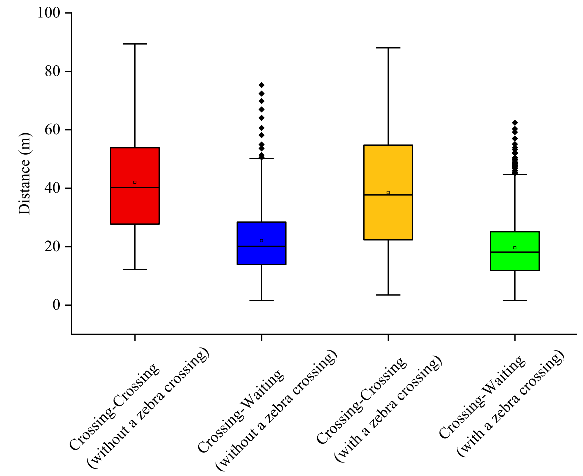
In this work, among the parameters that reflect pedestrian crossing intention, it is found that the value of the vehicle speed is much higher than the values of other parameters. Therefore, to improve the recognition accuracy and speed of the model, all the parameters were normalized.

Before parameters analysis, it should be pointed out that since the data collection were at the same site, even though the zebra crossing of this site has been removed, pedestrians and drivers may still believe that there is a zebra crossing in this location in a short time, which will affect pedestrian crossing behavior. In fact, the zebra crossing was removed during the period from April 14 to May 17. To minimize above effect, we removed the data collected between April 14 and 30 to give pedestrians a process of adaptation. We retained data without a zebra crossing from May 1 to May 17.

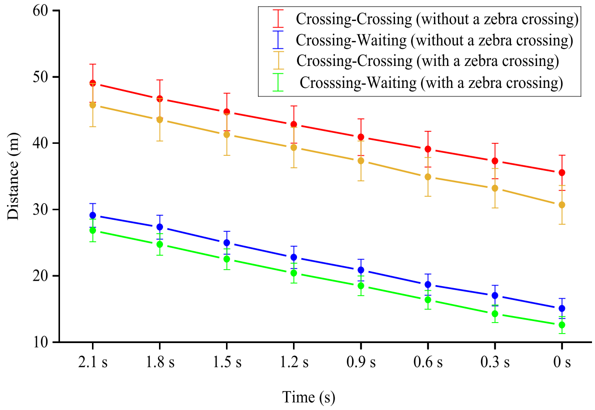
V. FEATURE PARAMETER ANALYSIS RESULTS

A. DISTANCE BETWEEN VEHICLE AND CROSSING AREA

Fig. 6(a) shows the box diagram of the distance between the vehicle and the crossing area before a pedestrian crossed under different road conditions and intentions (crossing-crossing and crossing-waiting). When the intention was crossing-crossing, the mean distance between the vehicle and crossing area in T seconds before a pedestrian crossed the street without the zebra crossing was 42.1 m, and that with the zebra crossing was 38.46 m. When the intention was crossing-waiting, the mean distance between the vehicle and crossing area before a pedestrian crossed the street without the zebra crossing was 22.0 m, and that with the zebra crossing was 19.59 m. It can therefore be concluded that, when the intention was crossing-crossing, the distance between the vehicle and the crossing area before a pedestrian crossed the street was generally higher than that when the intention was crossing-waiting.



(a) Mean distance between vehicles and the crossing area under different intentions and different road conditions

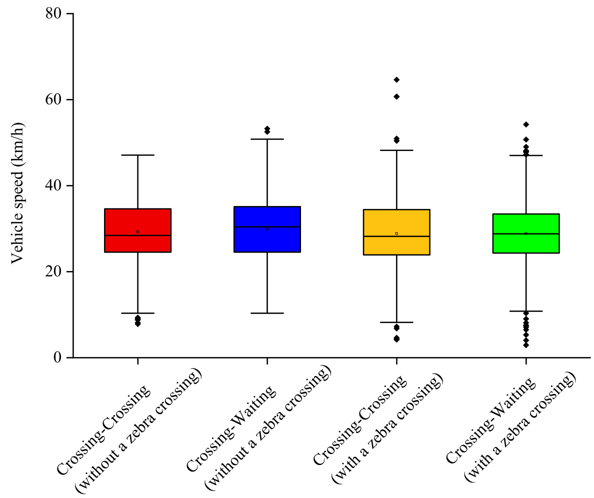


(b) Distance between vehicles and the crossing area at different times and with different intentions.

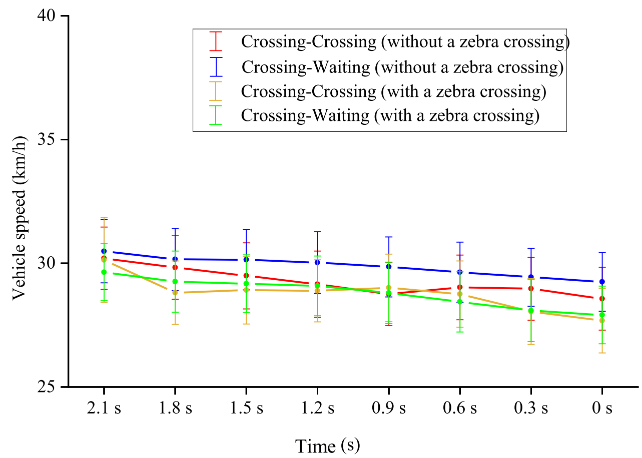
FIGURE 6. Distance between vehicles and the crossing area under different crossing intentions.

The results of a one-way ANOVA test showed that there were significant differences in the distance between the vehicle and crossing area before a pedestrian crossed the street under different intentions and road conditions ($F(3,3596) = 584.00$, $p < 0.001$). In this work, when post-hoc test is carried out, six pairwise comparisons are needed. After considering the p-value corrections (Bonferroni), when the post-hoc test was statistically significant, the judgment standard was adjusted as p value less than 0.0083 (0.05 / 6). The post-hoc test showed that when the intention was crossing-crossing, there was a significant difference in the distance between the vehicle and crossing area with and without a zebra crossing ($p < 0.0083$); The post-hoc test showed that when the intention was crossing-waiting, there was a significant difference in the distance between vehicle and crossing area with and without zebra crossing ($p=0.005 < 0.0083$). Moreover, the mean distance between the vehicle and crossing area under different crossing intentions was significantly different in the absence and presence of a zebra crossing ($p < 0.001$). When pedestrian intention is "Crossing-Crossing", the distance between vehicles and zebra crossing is larger.

Fig. 6(b) shows the change of the distance between the vehicle and crossing area in the first T seconds under different intentions and different road conditions. When there was no zebra crossing and the intention was crossing-crossing, the distance between the vehicle and crossing area was the highest, meanwhile, as time goes forward, the distance gradually decreases. In addition, when there was a zebra crossing and the intention was crossing-waiting, the distance curve is always at the bottom of all the curves. It can be clearly seen from Fig. 6(b) that the distance between the vehicle and the zebra crossing has a greater impact on pedestrians' crossing intentions. In addition, when there are pedestrians crossing the street with or without a zebra crossing, the distance between the vehicle and the zebra crossing is also different.



(a) Mean vehicle speed under different intentions and different road conditions.



(b) Vehicle speed at different times with different intentions.

FIGURE 7. Vehicle speed diagram under different crossing intentions.

B. VEHICLE SPEED

Fig. 7(a) presents the box diagram of the vehicle speed before crossing the street under different road conditions and different intentions. When the intention was crossing-crossing, the mean vehicle speed in the T seconds before the pedestrian crossed the street without a zebra crossing was 29.25 km/h, while that with a zebra crossing was 28.90 km/h. When the intention was crossing-waiting, the mean vehicle speed before the pedestrian crossed the street without a zebra crossing was 29.88 km/h, while that with a zebra crossing was 28.91 km/h. It can be seen that there is no significant difference in vehicle speed with different intentions and different road conditions.

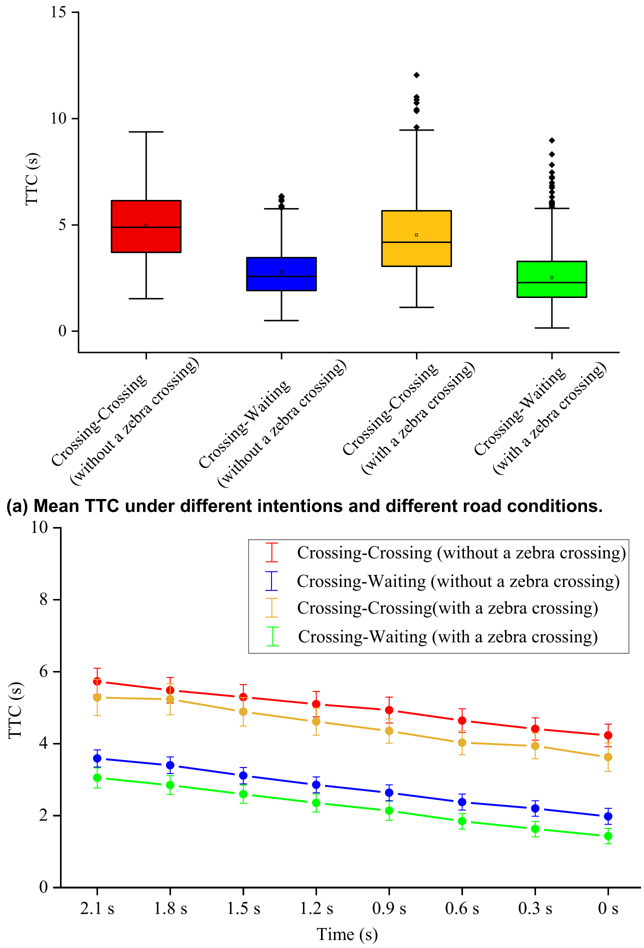
The results of a one-way ANOVA test showed that there were significant differences in the mean vehicle speed before the pedestrian crossed the street under different intentions and road conditions ($F(3,3596) = 2.04$, $p > 0.05$). The post-hoc test showed that when the intention was crossing-crossing, there was no significant difference in the vehicle speed while crossing the street with and without a zebra crossing ($p>0.0083$); this was also true when the intention was crossing-waiting ($p > 0.0083$). In addition, for both the presence and absence of a zebra crossing, the mean vehicle speed under different crossing intentions were no significant difference ($p>0.05$).

Fig. 7(b) presents the change of the vehicle speed in the first T seconds under different intentions and different road conditions. It can be seen from the four curves in the Fig. 7 that there was no difference in vehicle speed as time goes forward. This means that the parameter of vehicle speed has no effect on pedestrian crossing intentions.

C. TTC

Fig. 8(a) shows the box diagram of the TTC before a pedestrian crossed the street under different intentions (crossing-crossing and crossing - waiting) and different road conditions. When the intention was crossing-crossing, the mean TTC in the T seconds before a pedestrian crossed the street without a zebra crossing was 4.98 s, while that with a zebra crossing was 4.50 s. When the intention was crossing-waiting, the mean TTC before a pedestrian crossed the street was 2.77 s when there was no zebra crossing, while that with a zebra crossing was 2.45 s. It can therefore be concluded that, when the intention was crossing-crossing, the TTC before a pedestrian crossed the street was generally higher than that when the intention was crossing-waiting.

The results of a one-way ANOVA test showed that there were significant differences in the average TTC before a pedestrian crossed the street under different intentions and road conditions ($F(3,3596) = 780.95$, $p < 0.001$). The post-hoc test showed that when the intention was crossing-crossing, there was a significant difference in the TTC with and without a zebra crossing ($p < 0.0083$). The post-hoc test showed that when the intention was crossing-waiting, there was a significant difference in the TTC with and without zebra crossing ($p < 0.0083$). In addition, the mean TTC under different crossing intentions were significantly different in the presence and absence of a zebra crossing ($p < 0.001$). When pedestrian intention is "Crossing-Crossing", the TTC is larger.



(a) Mean TTC under different intentions and different road conditions.

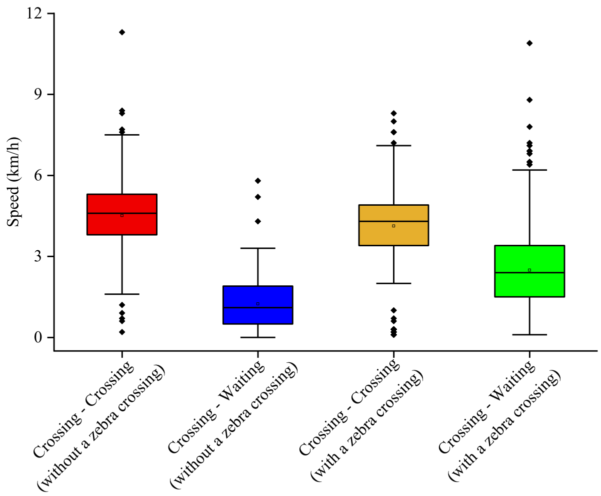
(b) TTC at different times and with different intentions.

FIGURE 8. TTC diagram under different crossing intentions.

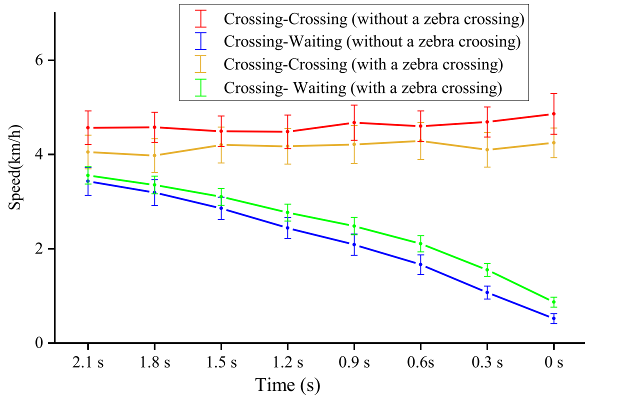
Fig. 8(b) shows the change of the TTC in the first T seconds under different intentions and different road conditions. When there was no zebra crossing and the intention was crossing-crossing, the TTC was the highest. In addition, when there was a zebra crossing and the intention was crossing-waiting, the TTC was the minimum. The curve changes under different combinations confirm that the TTC when pedestrians cross the street under different road conditions are quite different. In addition, it has been confirmed that TTC is an important parameter reflecting the intention of pedestrians to cross the street.

D. PEDESTRIAN SPEED

Fig. 9(a) shows the box diagram of the pedestrian speed before crossing the street under different intentions and different road conditions. When the intention was crossing-crossing, the mean pedestrian speed in the T seconds before crossing the street without a zebra crossing was 4.61 km/h, while that with a zebra crossing was 4.15 km/h. When the intention was crossing-waiting, the mean pedestrian speed before crossing the street without a zebra crossing was 2.16 km/h, while that with a zebra crossing was 2.48 km/h.



(a) Mean pedestrian speed under different intentions and road conditions.



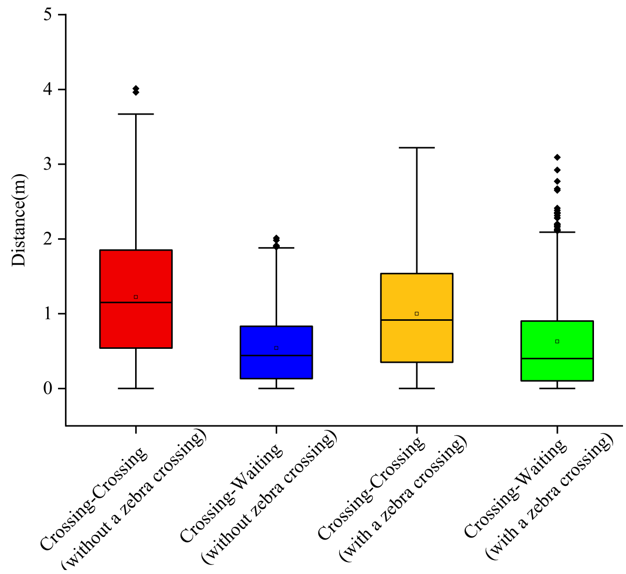
(b) Pedestrian speed at different times and with different intentions and conditions.

FIGURE 9. Pedestrian speed diagram under different crossing intentions and road conditions.

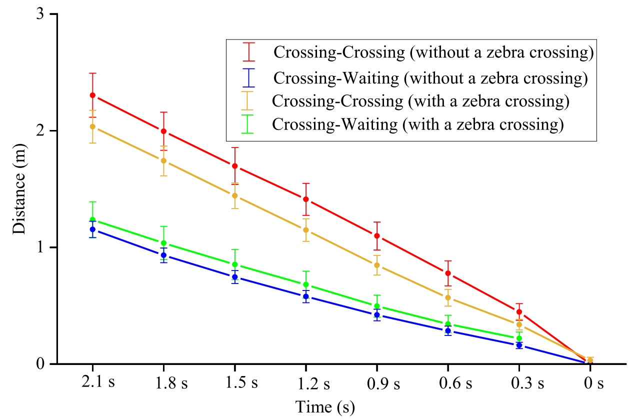
It can therefore be concluded that, when the intention was crossing-crossing, the pedestrian speed before crossing the street was generally higher than that when the intention was crossing-waiting.

The results of a one-way ANOVA test showed that there were significant differences in the mean pedestrian speed before crossing the street under different intentions and road conditions ($F(3,3596) = 1384.06$, $p < 0.001$). The post-hoc test showed that when the intention was crossing-crossing, there was a significant difference in the pedestrian speed while crossing the street with and without a zebra crossing ($p < 0.0083$); The post-hoc test showed that when the intention was crossing-waiting, there was a significant difference in the speed of pedestrians crossing the street with and without zebra crossing ($p < 0.0083$). In addition, for both the presence and absence of a zebra crossing, the average pedestrian crossing speeds under different crossing intentions were significantly different ($p < 0.001$). When pedestrian intention is "Crossing-Waiting", the pedestrian speed is smaller.

Fig. 9(b) shows the change of the pedestrian crossing speed in the first T seconds under different intentions and different road conditions. When there was no zebra crossing and the intention was crossing-crossing, the pedestrian speed was the highest. In addition, when there was no zebra crossing and the intention was crossing-waiting, the pedestrian speed was the minimum. It can be seen from the Fig. 9 that when pedestrians intend to wait, the speed of pedestrians decreases faster as time goes on. However, when pedestrians intend to cross, the pedestrian's speed tends to increase as time goes forward.



(a) Mean distance between pedestrians and crossing area under different crossing intentions and different road conditions.



(b) Distance between pedestrians and crossing area at different times and with different intentions.

FIGURE 10. Distance between pedestrians and crossing area under different crossing intentions.

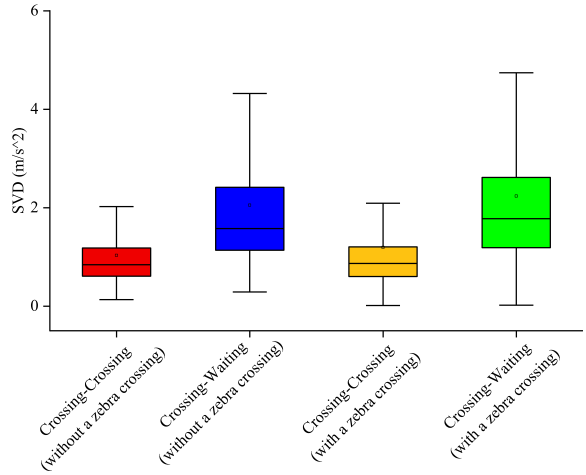
E. DISTANCE BETWEEN PEDESTRIAN AND THE CROSSING AREA

Fig. 10(a) shows the box diagram of the distance between pedestrians and the crossing area before crossing with or without a zebra crossing under different intentions. When the intention was crossing-crossing, the average distance between the pedestrians and the crossing area in the T seconds before the pedestrians crossed the street without a zebra crossing was 1.22 m, while that with a zebra crossing was

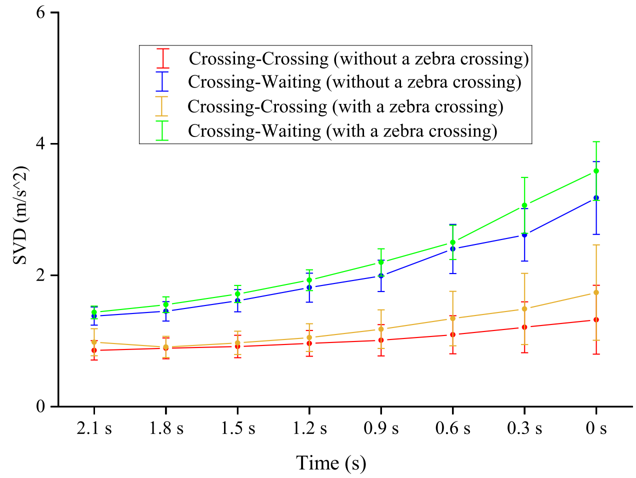
0.99 m. When the intention was crossing-waiting, the average distance between the pedestrians and crossing area before the pedestrians crossed the street without a zebra crossing was 0.54 m, while that with a zebra crossing was 0.63 m. It can therefore be concluded that, when the intention was crossing-crossing, the distance between the pedestrians and the crossing area before the pedestrians crossed the street was generally higher than that when the intention was crossing-waiting.

The results of a one-way ANOVA test showed that there were significant differences in the average distance between the pedestrians and crossing area before the pedestrians crossed the street under different intentions and road conditions ($F(3,3596) = 843.85$, $p < 0.001$). The post-hoc test showed that when the intention was crossing-crossing, there was a significant difference in the distance between the pedestrians and crossing area before the pedestrians crossed the street with and without a zebra crossing ($p < 0.0083$); this was also true when the intention was crossing-waiting ($p < 0.0083$). In addition, in both the absence and presence of a zebra crossing, the average distances between the pedestrians and crossing area under different crossing intentions were significantly different ($p < 0.001$). When pedestrian intention is "Crossing-Crossing", the distance between pedestrians and zebra crossing is larger.

Fig. 10(b) presents the distance between the pedestrians and the crossing area before the pedestrians crossed the street under different intentions and different road conditions. When there was no zebra crossing and the intention was crossing-crossing, the distance between the pedestrians and crossing area was the highest. In addition, when there was no zebra crossing and the intention was crossing-waiting, the distance between the pedestrians and crossing area was the minimum.



(a) The mean SVD under different crossing intentions and different road conditions.



(b) The SVD at different times and with different intentions.

FIGURE 11. **The SVD under different crossing intentions.**

F. SVD

Fig. 11(a) presents the box diagram of the SVD before the pedestrians crossed the street under different road conditions and different intentions. When the intention was crossing-crossing, the mean SVD in the T seconds before the pedestrians crossed the street without a zebra crossing was 1.02 m/s^2, while that with a zebra crossing was 1.20 m/s^2. When the intention was crossing-waiting, the mean SVD before the pedestrians crossed the street without a zebra crossing was 2.05 m/s^2, while that with a zebra crossing was 2.26 m/s^2. It can therefore be concluded that, when the intention was crossing-waiting, the SVD before the pedestrians crossed the street was generally higher than that when the intention was crossing-crossing.

The results of a one-way ANOVA test showed that there were significant differences in the mean SVD before the pedestrians crossed the street under different intentions and road conditions ($F(3,3596) = 250.45$, $p < 0.001$). The post-hoc test showed that when the intention was crossing-crossing, there was no significant difference in the SVD with and without a zebra crossing ($p=0.012 > 0.0083$); this was also true when the intention was crossing-waiting ($p < 0.0083$). In addition, in both the presence and absence of a zebra crossing, the average SVD under different crossing intentions were significantly different ($p < 0.001$). When pedestrian intention is "Crossing-Waiting", the SVD is larger.

Fig. 11(b) presents the change of the SVD in the first T seconds under different intentions and different road conditions. According to the four curves, SVD is relatively small when pedestrians intend to cross the street. When pedestrians intend to wait, SVD is relatively large. This is mainly because when the SVD is small, it means that the vehicle can stop without a large deceleration, so pedestrians have the intention of crossing street. On the contrary, when the SVD is large, the vehicle needs a large deceleration to stop, which is not safe for pedestrians, so pedestrians have the intention of waiting.

G. AGE, GENDER AND GROUP

Some studies [31]–[33] have pointed out that pedestrian age and gender have an important impact on pedestrian crossing behavior and decision-making. In order to improve the recognition accuracy of pedestrian crossing intention recognition model, we take pedestrian age and pedestrian gender as input variables to train the model. The pedestrians' age was divided. according to natural observation, using the classification method mentioned in the references which define 18–30 as a youth, 30–59 as middle age, and > 60 as old age [31], [34], [35]. Hashimoto *et al.* [25] found that individuals or groups have great differences in pedestrian crossing behavior, and uses this attribute as input variable to train the intention recognition model.

Through comparison, it can be found that there were substantial differences between the representative parameters of pedestrian crossing intention with or without the presence of a zebra crossing. In addition, via the parametric analysis results, it can be determined that the pedestrian speed, the pedestrian distance from the crossing area, the vehicle distance from the crossing area, the TTC, and SVD significantly affect pedestrian crossing intention. However, the vehicle speed was found to have no significant effect on pedestrian crossing intention, which is consistent with the findings of previous studies [36]. Therefore, the parameter set of pedestrian crossing intention was determined to consist of the following: the pedestrian speed, the distance between the pedestrian and the crossing area, the distance between the vehicle and the crossing area, the TTC, SVD, age, gender and group.

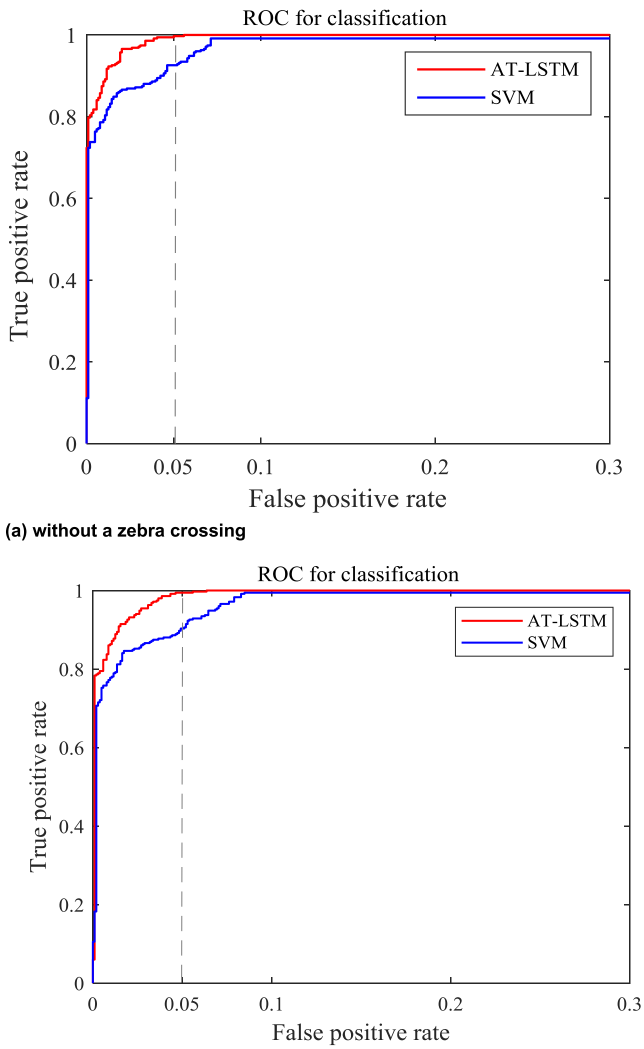
VI. MODEL ANALYSIS RESULTS

To ensure the balance of the data samples, 3600 data samples with and without a zebra crossing were selected, including 1800 samples with a zebra crossing and 1800 without a zebra crossing. For the data with a zebra crossing, the sample size was 900 for the crossing-crossing intention and 900 for the crossing-waiting intention. The sample distribution ratio of the data without a zebra crossing was the same.

Among all the samples, the training samples accounted for 60%, the validation samples accounted for 20%, and the remaining 20% of the samples were used as testing samples. In this work, the recognition of pedestrian crossing intention was considered to be a sequence problem. The pedestrian crossing intention was identified by a AT-LSTM, which has unique advantages in dealing with sequence problems, thereby ensuring the retention of useful information and the elimination of useless information. The model can effectively improve the recognition efficiency and accuracy. Therefore, in the model training, the LSTM algorithm based on the attention mechanism was used for the pedestrian crossing intention. According to the results of the fourth section, we take the pedestrian speed, the distance between the pedestrian and the crossing area, the distance between the vehicle and the crossing area, the TTC, SVD, age, gender and group as the input of the model. The input format is $[Dis_{ped}^{T}, Dis_{veh}^{T}, S_{ped}^{T}, TTC^{T}, SVD^{T}, \mathrm{Age}^{T}, \mathrm{Gender}^{T}, \mathrm{Group}^{T}]$.

TABLE 2. Model recognition accuracy 0 s in advance.

	Without a zebra crossing	With a zebra crossing
AT-LSTM	97.78%	97.22%
SVM	94.44%	93.33%



(a) without a zebra crossing

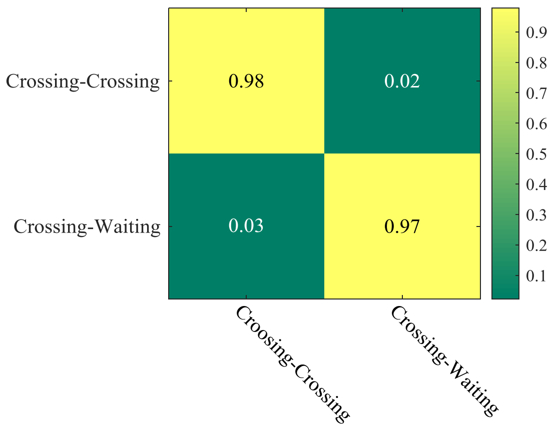
(b) with a zebra crossing.

FIGURE 12. ROC curves of model identification 0 s in advance.

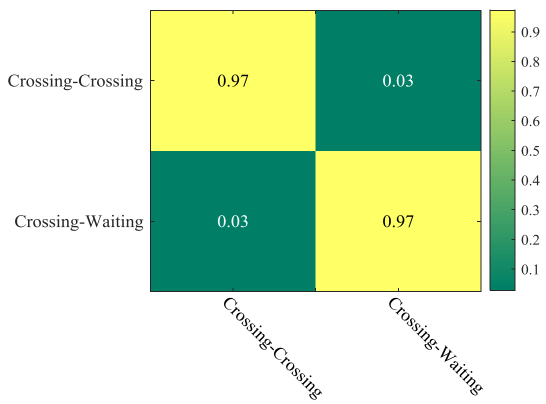
A. MODEL RECOGNITION RESULTS 0 s IN ADVANCE

The criteria of a pedestrian crossing intention recognition model are the recognition time, recognition accuracy, and model recognition lead time. If the recognition model can recognize the intention of a pedestrian to cross a street in advance and ensure the recognition accuracy, the model is considered to be excellent. The pedestrian crossing recognition model was first trained from time T to time 0; in other words, there was no advance time. As shown in Table 2, it was found that the intention recognition accuracy of the AT-LSTM model reached 97.22% when there was a zebra crossing and 97.78% when there was no zebra crossing. The intention recognition accuracy of the SVM model reached 93.33% when there was a zebra crossing and 94.44% when there was no zebra crossing. It can be seen that the AT-LSTM model has higher accuracy than SVM model in intention recognition. In addition, the calculation time of the model was obtained by the Toc/Tic function; it was found that the calculation time of the two models were fast, and the recognition time was less than 0.01 s.

Fig. 12(a) and Fig. 12(b) respectively present the receiver operating characteristic (ROC) curves without and with a zebra crossing. Via y = 0.05 in the Fig. 12, it can be determined that the two models had high recognition accuracy. In addition, it can be seen intuitively from the Fig. 12 that the recognition performance of the AT-LSTM model proposed in this paper is better than that of the SVM model.



(a) without a zebra crossing



(b) with a zebra crossing

FIGURE 13. Confusion matrixes for AT-LSTM model identification 0 s in advance.

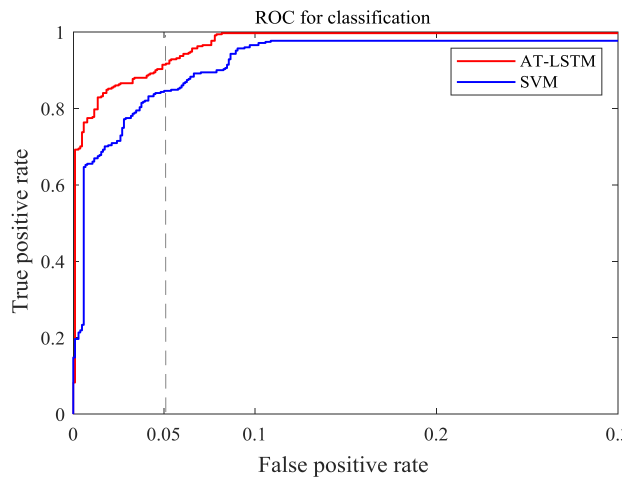
Fig. 13(a) and Fig. 13(b) respectively present the confusion matrixes without and with a zebra crossing, from which it can be concluded that the AT-LSTM model exhibited good recognition accuracy.

B. MODEL RECOGNITION RESULTS 0.6 s IN ADVANCE

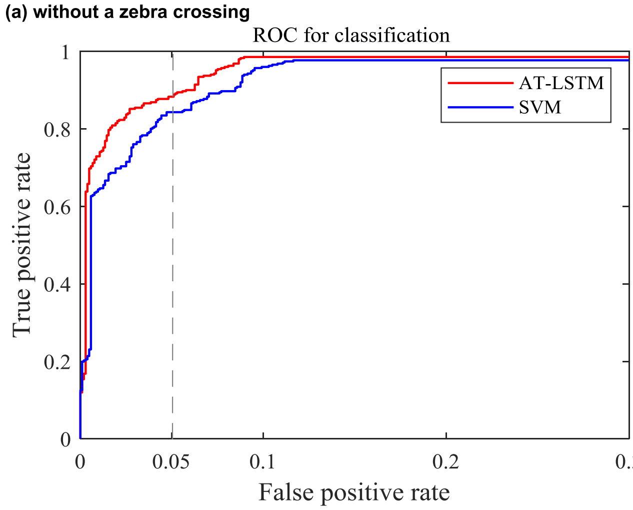
The pedestrian crossing recognition model was trained from time T to 0.6 s; in other words, the recognition time was 0.6 s in advance. As shown in Table 3, it was found that the intention recognition accuracy of the AT-LSTM model reached 93.05% when there was a zebra crossing and 93.89% when there was no zebra crossing. The intention recognition accuracy of the SVM model reached 90 % when there was a zebra crossing and 90.55% when there was no zebra crossing. It can be seen that the recognition accuracy of AT-LSTM model is better than that of SVM model. In addition, the calculation time of the two models were obtained by the Toc/Tic function; it was found that the calculation time was fast and the recognition time was less than 0.01 s.

TABLE 3. Model recognition accuracy 0.6 s in advance.

	Without a zebra crossing	With a zebra crossing
AT-LSTM	93.89%	93.05%
SVM	90.55%	90%



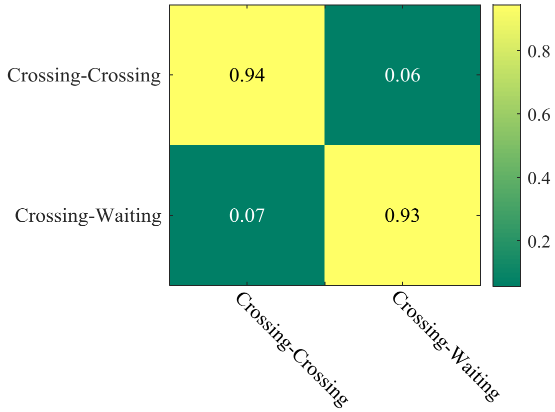
(a) without a zebra crossing



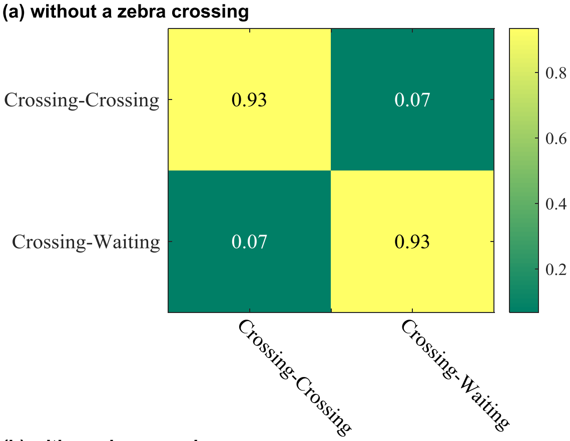
(b)with a zebra crossing

FIGURE 14. ROC curve of model identification 0.6 s in advance.

Fig. 14(a) and Fig. 14(b) respectively present the ROC curves without and with a zebra crossing at 0.6 s in advance. Via y = 0.05 in the Fig. 14, it can be determined that the model had high recognition accuracy. In addition, it can be seen intuitively from the Fig. 14 that the recognition performance of the AT-LSTM model proposed in this paper is better than that of the SVM model.



(a) without a zebra crossing



(b) with a zebra crossing.

FIGURE 15. Confusion matrix for AT-LSTM model identification 0.6 s in advance.

Fig. 15(a) and Fig. 15(b) respectively present the confusion matrixes with and without zebra crossing, from which it is evident that the AT-LSTM model exhibited good recognition accuracy.

C. MODEL PERFORMANCE EVALUATION

The performance of the two models for the recognition of pedestrian crossing intention 0 s in advance under different road conditions was evaluated by its precision, recall rate, and F1 score. The results are reported in Table 4. According to the model evaluation table, when the study site without a zebra crossing, the recognition performance of AT-LSTM model is better than that of SVM model. When the study site with a zebra crossing, the recognition performance of AT-LSTM model is also better than that of SVM model.

The performance of the two models for the recognition of pedestrian crossing intention 0.6 s in advance under different road condition were evaluated by its precision, recall rate, and F1 score. The results are shown in Table 5. According to the model evaluation table, the model recognition performance

TABLE 4. Model performance evaluation 0 s in advance.

	Precision	Recall Rate	F1 Score
AT-LSTM (without a zebra crossing)	97.25%	98.33%	97.79%
AT-LSTM (with a zebra crossing)	97.22 %	97.22%	97.22%
SVM (without a zebra crossing)	93.96%	95%	94.48%
SVM (with a zebra crossing)	93.82%	92.78%	93.29%

TABLE 5. Model performance evaluation 0.6 s in advance.

	Precision	Recall Rate	F1 Score
AT-LSTM (without a zebra crossing)	93.41%	94.44%	93.92%
AT-LSTM (with a zebra crossing)	92.82%	93.33%	93.07%
SVM (without a zebra crossing)	90.11%	91.11%	90.61%
SVM (with a zebra crossing)	89.56%	90.56%	90.05%

of AT-LSTM is better than that of SVM model. Although the performance of pedestrian crossing intention recognition at 0.6 s in advance was lower than that at 0 s in advance, on the whole, the performance of the intention recognition model under both road conditions was good.

VII. CONCLUSION

In this paper, the SVD and TTC were introduced based on original research, and it was found that both parameters can significantly affect pedestrian crossing intention. Furthermore, a more systematic and comprehensive parameter set was constructed to represent pedestrian crossing intentions, which has important practical significance for establishing a more accurate street crossing intention recognition model. This also lays a foundation for the improved driving safety of future autonomous vehicles.

At the same place, the differences between the parameters that represent pedestrian crossing intentions were respectively compared under the road conditions of the presence and absence of a zebra crossing. The results revealed that there was no significant difference in the vehicle speed in the absence and presence of a zebra crossing, and the vehicle speed was found to have no significant influence on pedestrian crossing intention. However, the other parameters that represent pedestrian crossing intention exhibited significant differences, and each has a significant influence on pedestrians' intentions to cross a street. Based on this conclusion, more refined identification models can be constructed for different road conditions, which is important for the driving safety of autonomous vehicles.

The pedestrian speed, pedestrian distance from the crossing area, vehicle distance from the crossing area, TTC, SVD, age, gender and group were used as model inputs. An AT-LSTM intention recognition model was established. The model exhibited good accuracy in recognizing pedestrian crossing intentions. Additionally, the model accurately recognizes the intentions of pedestrians 0.6 s in advance, which is extremely important for both automatic driving systems and assisted driving systems, as it will give them more time to react, thereby further ensuring both traffic safety and pedestrian safety.

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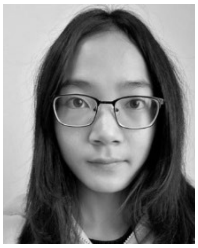

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