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Analyzing drivers' crossing decisions at unsignalized intersections in China

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ABSTRACT

In China, when two vehicle drivers encounter at an unsignalized intersection, almost neither of them completely stops the vehicle. Instead, one gradually approaches and dynamically makes a decision to either yield or preempt by gaming with the other vehicle. This process generates traffic conflicts and increases the probability of accidents. In this study, we aimed to study how straight-moving drivers made preemptive/yielding decisions when they encountered other drivers straight-moving across at unsignalized intersections. A total of 150 crossing cases were collected at an unsignalized intersection in Kunming City, China. By using detection program we made, motion parameters of the vehicles were extracted. Classification tree analysis was used to identify the decision moment of drivers and the major motion parameters that affected their decisions. Results showed that for crossing processes at unsignalized intersections in China, straight-moving drivers from the right side made preemptive/yielding decisions from 0.9 s to 1.3 s before reaching the crossing point. However, straight-moving drivers from the left side made decisions from 0.9 s to 1.2 s before reaching the crossing point. The speed difference between the two vehicles was the most important factor that affected a driver's decision-making. If the vehicle driver from the right side drove significantly slower than that from the left, then most drivers from the right side would yield to those from the left. On the contrary, if the vehicle driver from the right side drove significantly faster than that from the left, then most drivers from the right side would preempt those from the left. The findings of this study will help understand the decision-making patterns of drivers under crossing conditions, and thus provide suggestions to improve drivers' behavior at unsignalized intersections in China.

1. Introduction

Intersections are important hinge points, which join two or more roads. Traffic conflicts are easily generated in intersections. This makes many intersections to be accident black points, where traffic accidents are more likely to occur than anywhere else on the road. Traffic safety in intersections has attracted considerable research attention. National Highway Traffic Safety Administration (2009) statistical data showed that approximately 40% of the total 5,811,000 vehicle crashes in the US in 2008 occurred at intersections. The American Institute of Transportation Engineers asserted that road intersection safety was an important subject which should be studied closely (Elmitiny, Yan, Radwan, Russo, & Nashar, 2010).

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Although signalized intersections have been constructed widely, many unsignalized intersections are prevalent in both urban and rural areas. A popular tool used to control traffic at unsignalized intersections is the stop sign (Prasetijo & Ahmad, 2012). When there has no stop sign, the right-hand priority rule is used in most countries and regions (Bjorklund & Aberg, 2005; Elvik, Hoye, Vaa, & Sorensen, 2009). In China, road traffic rules indicate that when two straight-moving vehicles from different directions encounter at unsignalized intersections where no other traffic control is present, the straight-moving vehicle from the right side should have priority. Furthermore, between a straight-moving vehicle and a turning vehicle, the former holds the right of way. In China, however, neither of two vehicles that encounter at unsignalized intersections completely stops on the basis of priority rules. Rather, vehicle drivers gradually approach and dynamically make a decision to either yield or preempt. This uncertain process can bring in more traffic conflicts and increase the probability of accidents. Data show that the crash rate at unsignalized intersections in China is higher than those of other countries (Wang & Yang, 2008). NHTSA (2009) statistical data indicated that the number of crashes occurred at intersections with no traffic control device, with traffic signal, with stop sign, and unknown conditions were 3,474,000; 1,244,000; 571,000; and 522,000, respectively. In other words, approximately 70% of the total intersection crashes in the US occured at unsignalized intersections, compared to approximately 80% in China. Fatalities and injuries at unsignalized intersections in China accounted for approximately 13% of the total accident fatalities and 18% of the total accident injuries, whereas those at signalized intersections accounted for 5% and 7%, respectively (National Bureau of Statistics of China, 2009). In other words, the safety problem at unsignalized intersections is more serious than that at signalized intersections. In this regard, an analysis of drivers' crossing behavior is necessary to identify the main factors that affect drivers' decisions and thus correspondingly propose safety improvement measures for unsignalized intersections in China.

A field observation was conducted for eight hours daily to observe two vehicles' crossing condition at an unsignalized intersection (located at 25.05° north latitude, 102.74° east longitude) in Kunming City, China. Each direction of the intersection was a two-lane, two-way road. At this intersection, pedestrians, non-motor vehicles, and motor vehicles traveled together on the road. The results showed that 131 crossing decisions failed to follow priority rules to preempt or yield. This number accounted for 46.2% of the total crossing cases. Among all cases, the crossing behavior between one left-turning vehicle and one straight-moving vehicle accounted for 19.7%, whereas the crossing behavior between two straight-moving vehicles accounted for approximately 81.3%.

Thus, we aimed to study how straight-moving drivers make preemptive/yielding decisions when they encounter another straight-moving vehicle at unsignalized intersections. Most studies on crossing decisions (Becic, Manser, Creaser, & Donath, 2012; Guo & Lin, 2011; Hamed, Easa, & Batayneh, 1997; Hossain, 1999; Madanat, Cassidy, & Wang, 1994; Pollatschek, Polus, & Livneh, 2002; Spek, Wieringa, & Janssen, 2006) focused on drivers' gap acceptance. However, relatively few studies have been conducted on crossing decision moment and the main factors that affected drivers' decisions.

Therefore, in this study, we focused on when the straight-moving drivers completed their crossing decisions and what factors affected the drivers' decision-making.

The rest of the paper was structured as follows. The next section provided the background of the study. Then, the research method, including the observation site, data collection, and processing method, and the approach to analyze decision-making behavior were introduced. Section 4 discussed the decision moment and factors that affected drivers' decisions. Finally, data analysis results were discussed, and conclusions were made.

2. Literature review

Unsignalized intersections notably fail to provide an indication to drivers about when entry to intersections is appropriate. The crossing decision process of a driver at unsignalized intersections is more difficult than that at signalized intersections and can be considered "a complex and highly interactive process, whereby the driver makes individual decisions about when, where, and how to complete the required maneuver, subject to his/her perceptions of distances, velocities, and own car's performance" (TRB., 1997). Many studies have been conducted on the crossing decisions of drivers at unsignalized intersections. Most researchers have focused on the modeling of gap acceptance to describe crossing decisions (Becic et al., 2012; Guo & Lin, 2011; Hamed et al., 1997; Hossain, 1999; Madanat et al., 1994; Pollatschek et al., 2002; Spek et al., 2006). Besides, traffic conflict method has also been conducted on analyzing crossing decisions of drivers.

Furthermore, various mathematical methods, including fuzzy theory method, expert system, petri-network, and artificial neural network, have been applied to analyze decision behavior (Russell & Stuber, 1995; Tsguhide & Magnus, 2006; Wang & Yang, 2008; Yinghi & Hlaing, 2007). In this study, classification tree method was used to analyze drivers' crossing behavior decisions at unsignalized intersections.

2.1. Gap acceptance model

Gap acceptance studies mainly focused on two issues: determining the critical gap and analyzing the significant factors of gap acceptance behavior.

For instance, Drew (1968) assumed that the basis of a driver's crossing decision and behavior was the gap that he/she faced. The driver accepted the gap and moved across when the gap was larger than his/her critical gap. Otherwise, the driver would wait for an acceptable gap. In this study, the critical gap was assumed to be the same for all drivers. However, because the level of risk-taking and judgment of distances and vehicle speed used to determine the gap varies among drivers, drivers reacted differently to the same gap.

Madanat et al. (1994) used logit-modeling techniques to develop gap acceptance functions at a stop controlled intersection, as well as stochastic queuing theory to evaluate performance in intersections. The study considered that gap length, stop bar delay, queuing delay, and the number of rejected gaps were the significant predictors of gap acceptance behavior.

Basing on the risk evaluation associated with not accepting small gaps against the potential benefit of their acceptance, Pollatschek et al. (2002) presented a microscopic decision model for driver gap-acceptance behavior when drivers were waiting at an unsignalized intersection on a secondary road. The model estimated the resulting intersection capacity and considered individual preferences (risk loving vs. cautious). The results showed that different populations had different critical gaps. These differences resulted in different capacities on minor roads.

According to the earlier gap acceptance theory and preceding assumptions, Guo and Lin (2011) developed a survey designed method of rejected and accepted gaps and proposed four methods to calculate critical gap. By introduction of an exponentially rejected proportion function, the probability density function of the rejected and accepted gap was deduced. The relationship among the variables of these functions was analyzed. It was included that the exponential model of rejected proportion was more practical than the linear model. Typical capacity functions could be improved by using the accepted proportion function. McGowen and Stanley (2012) proposed an alternative model that was unbiased and could be used with naturalistic data to estimate the critical gap. The proposed model was compared with the Troutbeck and Brilon (1992) model through Monte-Carlo simulation. The results showed that the proposed model could estimate drivers' crossing decisions if a data set contained only one type of gap, or if the researcher wanted to throw out accepted gaps for fear of the maneuvering vehicle biasing the collected data.

Hamed et al. (1997) proposed a set of disaggregate models to indentify the main factors that influenced drivers' critical gap at unsignalized T-intersections, and then established a behavior model which could predict drivers' decision: either accept the gap and pass through the intersection or reject the gap and wait for the next one. This study showed that the significant variables affected gap acceptance were waiting time at the queue, driver's socioeconomic characteristics, and time of the day.

Although gap acceptance method has been applied and improved by many researchers, the method involves drawbacks (Brilon & Wu, 2002). One of limitations is the failure to consider driver behavior, particularly with regard to compliance with priority rules. Therefore, gap acceptance method cannot be used to explain the forced gap caused by aggressive driving behavior that does not accord with priority rules. The situation is worsened by heterogeneous traffic, which is a combination of motorized and non-motorized modes (Prasetijo, 2007).

2.2. Traffic conflict method

Conflict method was developed to overcome the problems in gap acceptance method. Brilon (2002) used the occupancy time and blocking time of vehicles at the conflict area to evaluate the crossing performance of drivers at unsignalized intersections. Xiao, Ran, Yang and Wang (2011) analyzed and modeled crossing decision behavior from the perspective of conflict avoidance by using the virtual field graph. After the preemptive level calculated was applied, a crossing behavior model that differentiated the conventional gap acceptance model was established. The results showed that a physiological critical preemptive level was necessary when drivers made decisions.

The aforementioned studies clearly explain or describe drivers' crossing behavior and decisions at unsignalized intersections in the US and Europe. However, the lack of control measures for right-of-way and yielding habits at unsignalized intersections, and gap-forcing behavior are common occurrences in China. Therefore, the results of some foreign studies may not be applicable to China. In addition, few studies have been conducted on crossing decision moment and the main factors that affected drivers' decisions. In this study, we therefore aimed to analyze, at unsignalized intersections in China, when drivers completed their preemptive/yielding decisions and what factors affected their decisions when they encountered conflicting vehicles.

2.3. Application of classification tree method

Classification trees or decision trees are among the popular statistical tools that emerged from the field of machine learning and data mining. Classification trees classify observations by recursively partitioning the predictor space. The resultant model can be expressed as a hierarchical tree structure. Especially since the introduction of the Classification and Regression Trees (CART) (Washington, Karlaftis, & Mannering, 2003), decision trees have received wide use in a variety of fields because of their non-parametric nature and easy interpretation (Kitsantas, Hollander, & Li, 2006; Lee, Chiu, Chou, & Lu, 2006).

In the traffic field, the application of decision trees is also extensive (Breiman, Friedman, Stone, & Olshen, 1984). For instance, Elmitiny et al., (2010) applied classification tree models to analyze how the probabilities of a stop or go decision and red-light running were associated with traffic parameters. Using 2005–2006 truck-involved accident data from national freeways in Taiwan, Chang and Chen (2012) developed a non-parametric decision tree model to establish the empirical relationship between injury severity outcomes and driver/vehicle characteristics, highway geometric variables, environmental characteristics, and accident variables. Juan de, Rocio de, and Calvo (2012) employed decision tree method to identify the key factors that affected bus transit quality of service and to compare the key attributes identified before and after passengers reflect on the main aspects of the system.

However, no study has been conducted to date on the classification analysis of drivers' crossing decisions at unsignalized intersections in China. In this study, we chose classification tree method to analyze the crossing decision moment and the main factors that affected drivers' decisions. SPSS software package (version 13.0; SPSS Inc., Chicago, IL, USA) was used to conduct classification tree analyses. These classification trees were developed on the basis of the CART approach. The Gini criterion was used as a measure of split criteria.

3. Method

3.1. Observation site

An urban unsignalized intersection (see Fig. 1) same to that in the observation site described in the Introduction was selected for this study. This intersection was a typical unsignalized intersection in China, where pedestrians, non-motor vehicles mixed with motor vehicles, traveled together on the road. Several types of crossing vehicles, such as buses, trucks, and passenger cars, traveled on the road as well. The speed limit at this intersection was 30 km/h (8.3 m/s). However, a high percentage of drivers did not follow traffic rules, and many exceeded the speed limit.

3.2. Data collection and processing

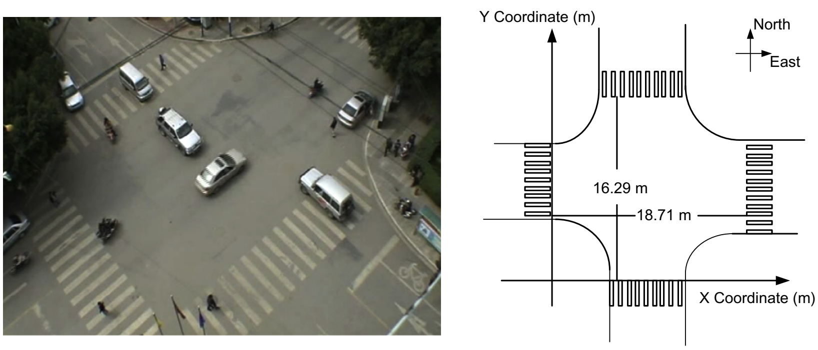
To obtain data for analysis, we chose a tall building on the south-west corner of the intersection and used a video-based system (Camera: SONY, Version: HDR-FX1000E, Pixel: 1.2-megapixel) to record drivers' preemptive/yielding decisions and traffic conditions. The frame rate of the camera was set as 25. Video recordings were made from 7 AM to 7 PM and lasted for seven days. The weather during the entire week was sunny, so the observation site had satisfactory visibility. Clear marking lines and an example of the traffic scenario can be seen in a screenshot from the recorded video (see Fig. 1a).

To study straight-moving drivers' preemptive/yielding decisions under crossing conditions, we chose 150 crossing cases, including two straight-moving vehicles from two different directions (all vehicles were passenger cars). To avoid the interference of other vehicles to drivers' decision making, we selected the simplest crossing case: one straight-moving vehicle encountered another straight-moving vehicle and no other objects. In this study, the straight-moving vehicle from the right side was noted as "the right vehicle," whereas the straight-moving vehicle from the left side was noted as "the left vehicle." Among all cases studied, 84 right vehicle drivers made preemptive decisions, whereas the remaining 66 right vehicle drivers made yielding decisions.

With the help of Open CV (Open Source Computer Vision Library, Version: Open CV 2.2) and its built-in algorithms, we made a program to process image sequences, which could automatically detect and track moving vehicles. After parameter calibration according to geometric data of the marking lines (see Fig. 1b), the program can extract and save the motion parameters of vehicles, such as the moving direction, position, velocity, and acceleration of vehicles. To reduce errors and estimate motion parameters accurately, Kalman filter was applied to process the data obtained. A previous study indicated that Kalman filter can increase the reliability of detected parameters reliable (Lu, Liu, Wang, & Tian, 2011).

Fig. 2 showed a preemptive case of a right vehicle. Fig. 2a and b presented the crossing condition and sketch of the process. Fig. 2c and d depicted the motion parameters of the two vehicles detected by the program in this case. Fig. 3 showed the same analysis of a yielding case.

Ten parameters (see Table 1) were finally selected for the data analysis in this study.



(a) The observed unsignalized intersection

(b) Geometric position of the marking lines

Fig. 1. The observation site.

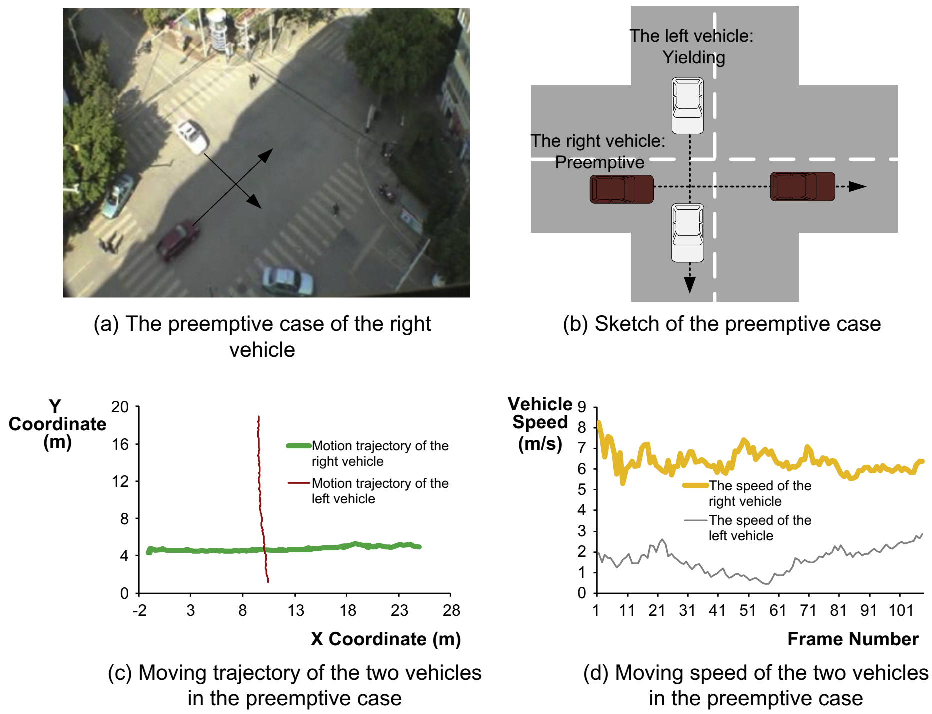


Fig. 2. A preemptive case and vehicle motion parameters detected.

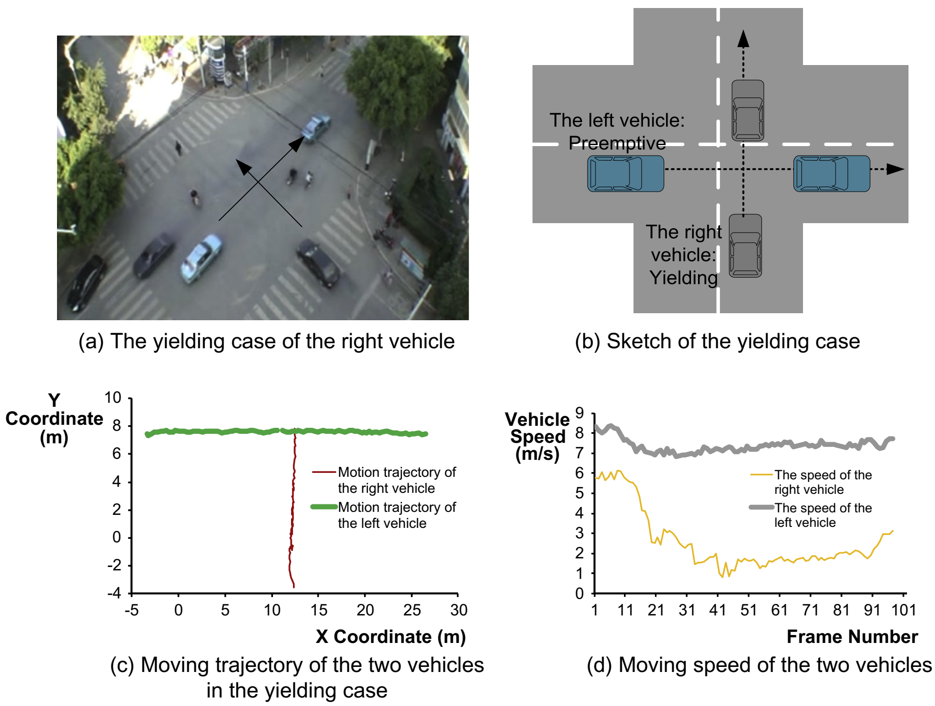


Fig. 3. A yielding case and vehicle motion parameters detected.

Among the 10 parameters, SPEED_R, SPEED_L, CROSS_TIME_R, CROSS_TIME_L, CROSS_DISTANCE_R, and CROSS_DISTANCE_L were the motion parameters of the vehicles. These parameters can affect drivers' preemptive/yielding decisions in crossing processes. SPEED_DIFFERENCE, DISTANCE, DISTANCE_DIFFERENCE, and TIME_DISTANCE represented the relative position or relative motion relationship between the two vehicles. These parameters were also important in studying drivers' decisions. Therefore, the 10 parameters were collected to analyze drivers' decision making.

The parameters SPEED_R, SPEED_L, SPEED_DIFFERENCE, and DISTANCE can be obtained from the video detection program, whereas the other parameters needed to be calculated according to the position of the crossing point.

How was the position of the crossing point defined? In this study, the crossing point was determined by the trajectory information of the two vehicles and the crossing position of the two trajectories was defined as the crossing point. Fig. 4 showed that the trajectories of the two vehicles were drawn by (x, y) coordinates at each moment. Then, crossing point A can be obtained. That was, when the center of mass of vehicle A arrived at point A, the vehicle reached the crossing point.

Knowing the position of the two straight-moving vehicles that reached the crossing point and the coordinates of the two vehicles at each moment, CROSS_DISTANCE_R and CROSS_DISTANCE_L could be calculated. DISTANCE_DIFFERENCE was obtained by subtraction of CROSS_DISTANCE_L from CROSS_DISTANCE_R. Assuming that the two vehicles kept moving with the current motion state, CROSS_TIME_R and CROSS_TIME_L can be calculated by division of CROSS_DISTANCE_R by SPEED_R and CROSS_DISTANCE_L by SPEED_L, respectively. TIME_DISTANCE was obtained by subtraction of CROSS_TIME_L from CROSS_TIME_R. All parameters in Table 1 can be derived by the program and calculation method mentioned above.

3.3. Decision-making analysis method

In this study, we conducted decision trees analysis by using SPSS software package (Version: 13.0). The decision-making analysis method was described as follows:

First, the right driver's decision results were taken as a dependent variable. "0" represented the condition when the right vehicle was yielding and "1" when the right vehicle was preemptive. The parameters (see in Table 1) of the two vehicles in each case of each moment before the right vehicle reached the crossing point were obtained, and then the data were gathered. The accuracy percentage of the classification at each moment was determined with decision tree classification for the data obtained. Then, the decision moment can be analyzed according to the distribution of the accuracy percentage. The period that had the highest accuracy percentage was examined and noted as "P_H period." According to the features of the decision trees analysis, the parameters in P_H period had a close relationship with the drivers' decisions. Then, the data in P_H period can be gathered, and decision trees analysis was performed again. The analysis for root node and leaf nodes in the decision tree results can obtain the main factors that affected the right drivers' decision. Additional detailed descriptions of these decision tree algorithms were beyond the scope of the present study. For further discussions of the tree methodology, please refer to the study of Breiman et al. (1984).

Second, the decision results of left drivers were taken as dependent variables. "0" represented the condition when the left vehicle was yielding and "1" when the left vehicle was preemptive. The parameters of the two vehicles in each case of each moment were obtained before the left vehicle reached the crossing point. With the use of the same method described above, the accuracy percentage of the left drivers at each moment and the main factors that affected their decisions can be acquired.

4. Results

4.1. Determination of the decision moment

One hundred and fifty crossing cases, including right and left vehicles, were selected in this study. In each case, the parameters (see Table 1) of both right and left vehicles were extracted from 0.2 s to 2.0 s (time interval: 0.1 s) before the right vehicle reached the crossing point. The same parameters were extracted from 0.2 s to 2.0 s before the left vehicle reached the crossing point.

Section 3.3 (decision-making analysis method) indicated that the accuracy percentage of the decision tree classification for right and left vehicles at each moment was determined in Fig. 5.

Table 1
Parameters influencing preemptive/yielding decisions in crossing process.

Parameters	Definition
SPEED_R	Speed of the right vehicle
SPEED_L	Speed of the left vehicle
SPEED_DIFFERENCE	The relative speed between the right vehicle and the left vehicle
DISTANCE	The relative distance between the right and left vehicles
CROSS_DISTANCE_R	Distance between the right vehicle to the crossing point
CROSS_TIME_R	The travel time of right vehicle to encounter the crossing point
CROSS_DISTANCE_L	Distance between the left vehicle to the crossing point
CROSS_TIME_L	The travel time of left vehicle to encounter the crossing point
DISTANCE_DIFFERENCE	The relative distance between the right vehicle to the crossing point and the left vehicle to the crossing point
TIME_DISTANCE	The amount of time between when the right vehicle crosses the crossing point and when the left vehicle crosses the crossing point

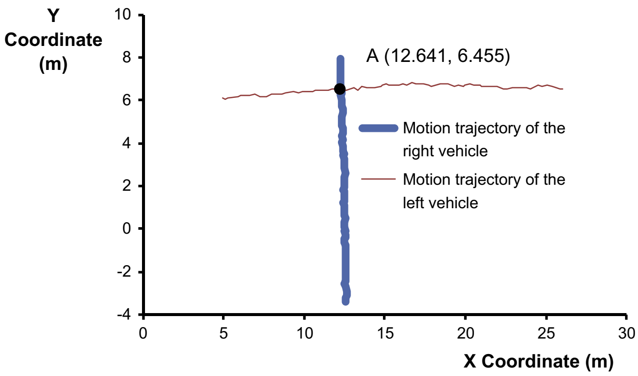


Fig. 4. The crossing position of the two vehicles.

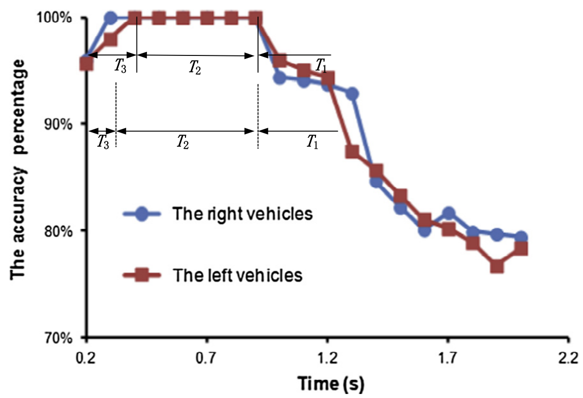


Fig. 5. The accuracy percentage of decision trees classification at each moment.

Previous research showed that in actual driving processes, drivers' behavior can be divided into three stages: information perception, trajectory decision, and operation correction (Boer, 1999; Kaysi & Abbany, 2007).

For the crossing process including two straight-moving vehicles at an unsignalized intersection, drivers usually make their trajectory decisions on the basis of their information perception of the concurrent traffic environment and other vehicles' movements. In this study, the period from perceiving the information to making an ideal trajectory decision was considered as the trajectory decision period, which was noted as "T_1." Because of the delay in drivers' reaction, it needed a period of time from drivers completed trajectory decisions to their actual operation on vehicles. We considered this period as the reaction period, which was noted as "T_2." Then, the drivers would continuously correct their operation until the crossing process was completed. This period was considered as the drivers' correction-operation period, which was recorded as "T_3." The parameter data in period "T_2" significantly affected the drivers' correction-operation in period "T_3" and the results of the drivers' crossing decisions. The accuracy percentage of decision classification was highest if the data in period "T_2" was used in the decision trees analysis.

Fig. 5 showed that for the right vehicle drivers, the P_H was from 0.3 s to 0.9 s before reaching the crossing point. Illustrating that the reaction period (T_2) of the right drivers was 0.3 s to 0.9 s before reaching the crossing point. Therefore, the correction-operation period (T_3) of the right vehicle drivers was from 0 s to 0.3 s before reaching the crossing point. The trajectory decision period (T_1) was from perceiving information to 0.9 s before reaching the crossing point. Fig. 6 also showed that the correction percentage of decision classification was greater than 90% from 0.9 s to 1.3 s and dropped rapidly from 1.3 s to 2.0 s before reaching the crossing position. Therefore, it could be inferred that the right vehicle drivers completed their decisions from 0.9 s to 1.3 s before reaching the crossing point. In other words, the decision moment of the right drivers was from 0.9 s to 1.3 s before reaching the crossing point.

Fig. 5 showed that the P_H period of the left vehicle drivers was from 0.4 s to 0.9 s before reaching the crossing point. This result indicated that the reaction period (T_2) of the left vehicle drivers was from 0.4 s to 0.9 s before reaching the crossing point. Therefore, the correction-operation period (T_3) of the left vehicle drivers was from 0 s to 0.4 s before reaching the crossing point. The trajectory decision period (T_1) was from perceiving information to 0.9 s before reaching the crossing point. Fig. 6 shows that the correction percentage of decision classification was greater than 90% from 0.9 s to 1.2 s and dropped rapidly from 1.2 s to 2.0 s before reaching the crossing point. Therefore, we considered that the left vehicle drivers

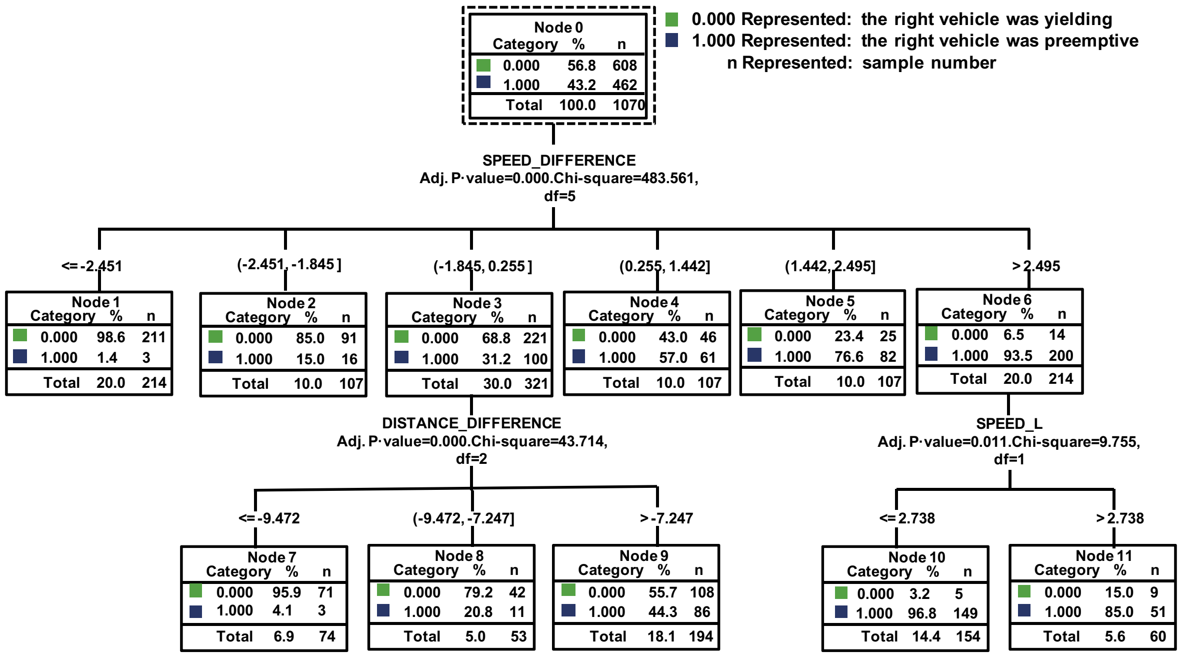


Fig. 6. The result of decision trees analysis for the right drivers.

completed their decisions from 0.9 s to 1.2 s before reaching the crossing point. That is, the decision time of the left drivers was between 0.9 s and 1.2 s before reaching the crossing point.

T-test was conducted to determine whether a significant difference exists in the decision time between left and right drivers. The results showed no significant difference in decision time between the two groups ($p = 0.698$).

4.2. Factors influencing drivers' decision-making behaviors

4.2.1. Right drivers

For the right drivers, we gathered the data in this period and conducted decision tree analysis again because the P_H period was from 0.3 s to 0.9 s before reaching the crossing point. Fig. 6 illustrated the classification tree diagram for right drivers' preemptive/yielding decision model. In the diagram, "0" represented the condition in which the right vehicle was yielding, and "1" represented the condition in which the right vehicle was preemptive. The classification tree diagram included nine terminal nodes, which generated the following classification rules for the right drivers' preemptive/yielding decision:

(1) If the SPEED_DIFFERENCE was lower than −1.845 m/s, that is, if the right vehicle driver was driving more than 1.845 m/s slower than the left vehicle driver, then most right drivers (larger than 85.0%) would yield to left drivers.
(2) If the SPEED_DIFFERENCE was higher than 2.495 m/s, that is, if the right vehicle driver was driving more than 2.495 m/s higher than the left vehicle driver, then most right drivers (93.5%) would preempt left drivers. Under this condition, SPEED_L also affected the drivers' preemptive/yielding decisions.
(3) If the SPEED_DIFFERENCE was between −1.845 m/s and 0.255 m/s, that is, if the right vehicle driver was driving less than 1.845 m/s slower or less than 0.255 m/s higher than the left vehicle driver, then the DISTANCE_DIFFERENCE would affect the drivers' decisions. Different ranges of DISTANCE_DIFFERENCE would result in different decisions. If the DISTANCE_DIFFERENCE was less than −9.472 m (a negative value indicated that the distance between the left vehicle to the crossing point was longer than the distance between the right vehicle to the crossing point), then 95.9% of right drivers would yield to left drivers. If the DISTANCE_DIFFERENCE was more than −9.472 m, less than 80% of right drivers would yield to left drivers.

Additionally, Fig. 7 showed the importance of the independent variable to right drivers' preemptive/yielding decision model. According to the order of importance of parameters in the figure, SPEED_DIFFERENCE was the most important variable that predicted drivers' preemptive/yielding decisions. DISTANCE_DIFFERENCE and SPEED_L were less significant.

4.2.2. Left drivers

We also gathered the data in this period and performed decision trees analysis for left vehicle drivers because the P_H period was from 0.4 s to 0.9 s before reaching the crossing point. Fig. 8 illustrated the classification tree diagram for left drivers'

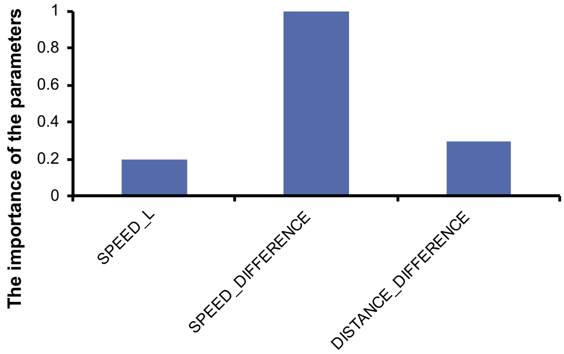


Fig. 7. Importance of the independent variable to the right drivers' decisions.

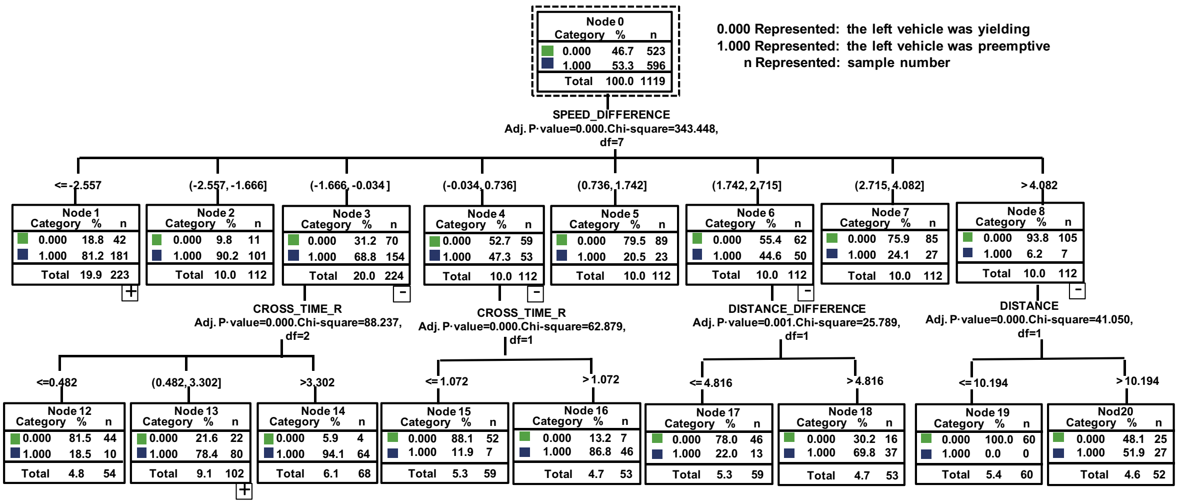


Fig. 8. The result of decision trees analysis for the left drivers.

preemptive/yielding decision model. In the diagram, "0" represented the condition in which the left vehicle was yielding, and "1" represented the condition in which the left vehicle was preemptive. The classification tree diagram included 10 terminal nodes, which generated the following classification rules for left drivers' preemptive/yielding decision:

(1) If the SPEED_DIFFERENCE was lower than −2.557 m/s, that is, if the left vehicle driver was driving more than 2.557 m/s higher than the right vehicle driver, then 81.2% of left drivers would preempt to right drivers. Under this condition, CROSS_DISTANCE_R also affected the driver's decisions. Different ranges of CROSS_DISTANCE_R would result in different decisions.
(2) If the SPEED_DIFFERENCE was between −2.557 m/s and −1.666 m/s, that is, if the left vehicle driver was driving more than 1.666 m/s and less than 2.557 m/s higher than the right vehicle driver, then most left drivers (90.2%) would preempt to right drivers.
(3) If the SPEED_DIFFERENCE was between −1.666 m/s and 0.736 m/s, that is, if the left vehicle driver was driving less than 1.666 m/s higher and less than 0.736 m/s slower than the right vehicle driver, then CROSS_TIME_R would affect the drivers' decisions. Drivers would make their preemptive/yielding decisions on the basis of CROSS_TIME_R.
(4) If the SPEED_DIFFERENCE was between 1.742 m/s and 4.082 m/s, that is, if the left vehicle driver was driving more than 1.742 m/s and less than 4.082 m/s slower than the right vehicle driver, then the DISTANCE_DIFFERENCE or DISTANCE would affect the drivers' decisions.
(5) If the SPEED_DIFFERENCE was higher than 4.082 m/s, that is, if the left vehicle driver was driving more than 4.082 m/s slower than the right vehicle driver, then most left drivers (93.8%) would make yielding decisions when they encountered right vehicles at unsignalized intersections.

Additionally, Fig. 9 showed the importance of the independent variable to the left drivers' preemptive/yielding decision model. According to the order of importance of parameters in the figure, SPEED_DIFFERENCE was also the most important variable that predicted drivers' preemptive/yielding decisions. CROSS_TIME_R, DISTANCE, and DISTANCE_DIFFERENCE were less significant.

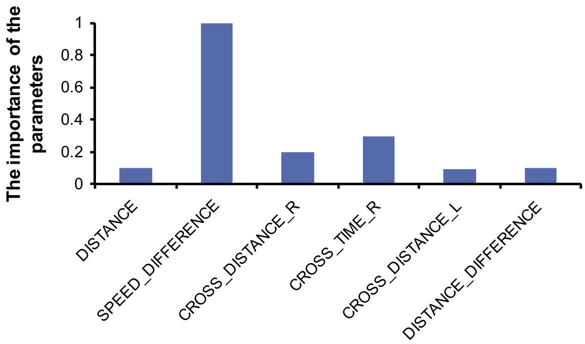


Fig. 9. Importance of the independent variable to the left drivers' decisions.

5. Discussion

Previous decision-making theory showed that under actual driving processes, drivers' behavior can be categorized into three stages: information perception, trajectory decision, and operation correction (Boer, 1999; Kaysi & Abbany, 2007). On the basis of this theory, we divided drivers' behavior into three sections in this study, including trajectory decision period, the reaction period, correction-operation period, and then analyzed the time spent in each of these sections by using decision tree. Among them, the trajectory decision period included information perception and trajectory decision. Considering about the reaction delay of drivers, we added reaction period into the decision-making behavior process. The analysis in this article can help us to better understand the decision-making patterns and the actual drivers' behavior at unsignalized intersections in China.

The drivers' reaction time has been investigated by some studies (Ge, Zhang, & Wang, 2010; Setti, Rakha, & El-Shawarby, 2006; Wu, Yuan, Chen, & Li, 2009). In this paper, the drivers' reaction period was also been analyzed. The results showed that the drivers' reaction time obtained by our study was similar to those of previous studies. Furthermore, such a finding indicated that the drivers took a certain amount of reaction time before completing their actual preemptive/yielding operations. This consistency in results strengthened the validity and accuracy of our study.

HCM. (2000) and its technical report entitled "Capacity and Level of Service at Unsignalized Intersections," as well as A Policy on Geometric Design Highway and Street (2001) and its technical support report entitled "Intersection Sight Distance" (NCHRP, 1996), studied the critical gap acceptance of each vehicle. Our study determined the crossing decision time of the drivers. The comparison showed that crossing decision time in this study was less than the critical gap acceptance obtained by previous studies in the US. Therefore, it can be inferred that the straight-moving drivers in China had failed in giving way voluntarily at unsignalized intersections. For the two straight-moving drivers under crossing conditions, there had an obvious game relation between them.

According to the order of importance of the parameters shown in Figs. 7 and 9, the most important variable that predicted two drivers' decisions was the difference in speed between the left and right vehicle drivers. If the right vehicle driver was going significantly slower than the left vehicle driver, then most right drivers would yield to left drivers. On the contrary, if the right vehicle driver was going significantly faster than the left vehicle driver, then most right drivers would preempt left drivers. For two straight-moving drivers' crossing process, each driver would estimate his/her own and the other driver's speed and then made a crossing decision. If we want to control right/left drivers' preemptive/yielding decisions, an effective method will be to control the speed of left/right vehicles entering the intersection.

6. Conclusion

We investigated how straight-moving drivers made their preemptive/yielding decisions when they encounter another vehicle moving across at unsignalized intersections. We also analyzed drivers' decision moment and the main factors that affected drivers' decisions. Our conclusions were as follows:

(1) Straight-moving vehicle drivers from the right side completed their preemptive/yielding decisions from 0.9 s to 1.3 s before reaching the crossing point. However, straight-moving vehicle drivers from the left side completed their preemptive/yielding decisions from 0.9 s to 1.2 s before reaching the crossing point.
(2) The most important variable that predicted two drivers' decisions was the difference in speed between the left and right vehicle drivers. However, DISTANCE_DIFFERENCE (i.e., the relative distance between the right vehicle to the crossing point and the left vehicle to the crossing point), SPEED_L (i.e., speed of the left vehicle), CROSS_TIME_R (i.e., the travel time of the right vehicle to encounter the crossing point), and DISTANCE (i.e., the relative distance between the right and left vehicles) also affected the drivers' decisions.

(3) This study was beneficial in that the results shed light on the crossing decisions of drivers, guided the formation of recommendations to control drivers' behavior, and helped ensure traffic safety at unsignalized intersections in China. In addition, this study can provide parameters to establish a decision model that is suitable to China's conditions.
(4) The analysis in this study contributed to our understanding of the decision-making patterns and drivers' behavior in China.

Nevertheless, this study had limitations. The effects of geometric design, capacity of the intersection, and personal characteristics of drivers on decision making were not considered in the decision-making analysis. Only the simplest crossing cases, in which one straight-moving driver encountered another straight-moving vehicle, were selected to analyze the crossing decisions of drivers. We did not study crossing decisions when one straight-moving vehicle encountered two or more vehicles (from different directions). In addition, a single, unsignalized intersection was chosen to identify the common features in crossing decisions.

For future research, we will examine additional intersections that can satisfy the requirement of capturing the panoramic scene to analyze the effects of complex traffic situations and factors (e.g., geometric design, capacity of the intersection, and personal characteristics of drivers) on drivers' crossing decisions.

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