Investigating and Modeling Motorized and Non-Motorized Interaction Behavior in Shared Spaces of Intersections

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Outline

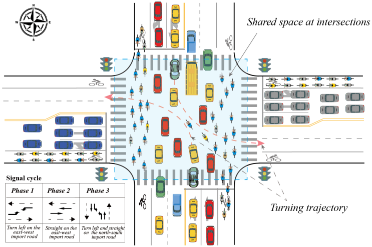
Motivation

Motivation

- Backgrounds
- Research Gaps

Backgrounds

- What is the shared space?



- Why study intersection shared spaces?
  - High rate of motorized and non-motorized collisions.
  - There are significant challenges for self-driving vehicles in complex interaction environments.
  - Lack of elaborate management strategies for proactive safety control.
- What is an intersection shared space?

Existing studies

Econometric and statistical models

An analysis of factors influencing conflict risk based on an econometric statistical model. Both the time of risk exposure and the level of risk are selected as dependent variables. The analysis methods are linear regression model, Logit (liu et al.,2015) , random effects, Poisson model, extreme value model (Fu et al.,2022), etc.

Machine learning models

"Black-box" prediction, which do not require clear relationships between variables, have a strong learning ability and can accurately predict the risk state.

Research gaps

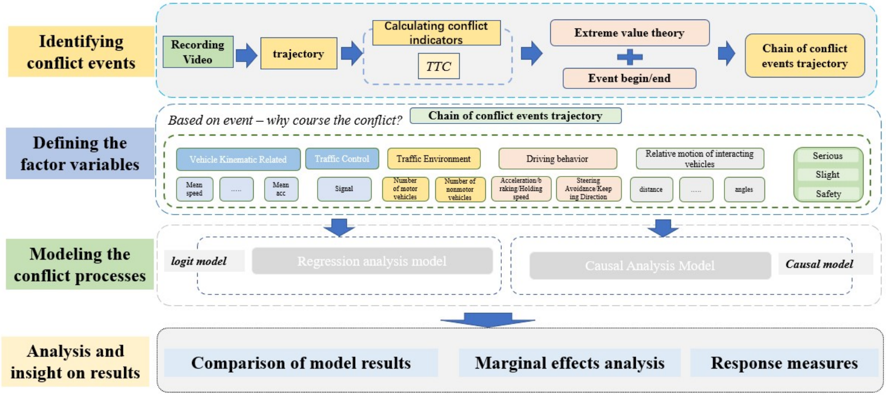
- It is difficult to reflect the dynamic process of risk transition, and the accuracy of risk prediction is low.
- It is hard to identify the key causal factors and lack of causal link analysis.

To establish a conflict risk evolution model for the interaction process between motorized and non-motorized vehicles, to clarify the conflict causal chain, and to identify the core causes of conflict.

Methodology

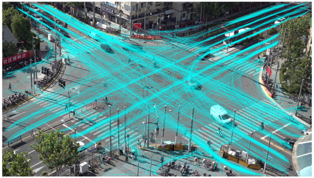
Methodology

Flowchart

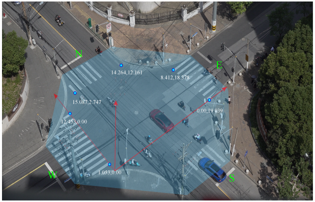

Identifying conflict events
Recording Video
trajectory
Calculating conflict indicators
TTC
Extreme value theory
Event begin/end
Chain of conflict events trajectory
Defining the factor variables
Based on event – why course the conflict?
Chain of conflict events trajectory
Vehicle Kinematic Related
Traffic Control
Traffic Environment
Driving behavior
Relative motion of interacting vehicles
Mean speed
.....
Mean acc
Signal
Number of motor vehicles
Number of nonmotor vehicles
Acceleration/braking/Holding speed
Steering Avoidance/Keeping Direction
distance
.....
angles
Serious
Slight
Safety
Modeling the conflict processes
logit model
Regression analysis model
Causal Analysis Model
Causal model
Analysis and insight on results
Comparison of model results
Marginal effects analysis
Response measures

Extracting and reconstructing trajectories

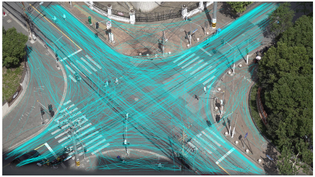
Longchang-Changyang intersection



Trajectory of Longchang-Changyang



Longchang-Changyang intersection



Trajectory of Ningwu-Hejian

Yolov7+Deepsort is used to extract each type of vehicle trajectory data, and the SFPF Algorithm that is proposed in the previous research is applied to reconstruct the missing and noisy trajectories.

Extract the Conflict Chain

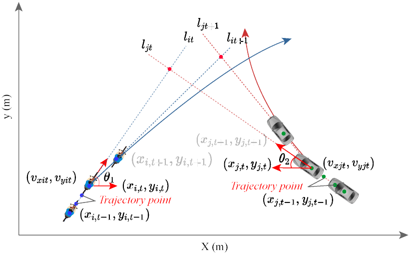
- Calculate conflict points

$$x_{it} = \frac{(y_2 - y_1) - (x_2 \cdot \tan\theta_2 - x_1 \cdot \tan\theta_1)}{\tan\theta_1 - \tan\theta_2} \quad (1)$$

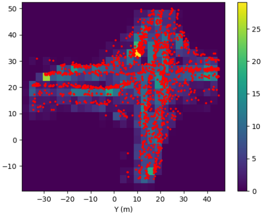
$$y_{it} = \frac{(x_2 - x_1) - (y_2 \cdot \cot\theta_2 - y_1 \cdot \cot\theta_1)}{\cot\theta_1 - \cot\theta_2} \quad (2)$$

- Calculation of conflict time

$$|TX_1 - TX_2| < \sigma \quad (3)$$



Process diagram of conflict between MV and NMV



Heat Map of Conflict Point Distribution($ttc < 5s$)

- Define the Variable

Variable type	variable name	variable encoding	Variable Definition	amount	Percentage
Conflict level	ttc(s)	ttc1	[5,∞)	241	14.07
		ttc2	[3,5)	374	21.83
		ttc3	[2,3)	475	27.73
		ttc4	[1,2)	592	34.56
		ttc5	[0,1)	31	1.81
Driving Purpose	fdir	fdir1	Left turning	107	12.75
		fdir2	straight	364	43.38
		fdir3	Left turning	368	43.86
	sdir	sdir1	Left turning	397	47.32
		sdir2	straight	422	50.30
		sdir3	Left turning	20	2.38
Vehicle Movement Status	fs (m/s)	fs1	[0,4]	392	46.72
		fs2	(4,8]	408	48.63
		fs3	(8,12]	39	4.65
	faa (m/s^2)	faa1	(−∞,-5]	1	0.12
		faa2	(-5,0]	375	44.70
		faa3	(0,5]	463	55.18
	ftc(m)	ftc1	[0,5]	347	41.36
		ftc2	(5,15]	338	40.29
		ftc3	(15,30]	111	13.23
		ftc4	(30,+∞)	43	5.13
	ss (m/s)	ss1	[0,4]	422	50.30
		ss2	(4,8]	405	48.27
		ss3	(8,12]	12	1.43
	saa(m/s^2)	saa1	(−∞,0]	402	47.91
		saa2	(0,5]	437	52.09
	stc(m)	stc1	[0,5]	356	42.43
		stc2	(5,15]	341	40.64
		stc3	(15,30]	99	11.80
		stc4	(30,+∞)	43	5.13
Traffic environment	fnn	fnn1	(0,1)	377	44.93
		fnn2	[1,3]	433	51.61
		fnn3	(3,+∞)	29	3.46
	fmn	fmn1	(0,1)	377	44.93
		fmn2	[1,3]	433	51.61
		fmn3	(3,+∞)	29	3.46
	snn	snn1	(0,1)	620	73.9
		snn2	[1,3]	219	26.1
	smn	smn1	(0,1)	625	73.3
		smn2	[1,3]	224	26.7

- Define the Variable

Variable type	variable name	variable encoding	Variable Definition	amount	Percentage
	fba	fba1	continue direction	648	77.23
		fba2	evasive behavior	191	22.77
		fbeh1	Constant acceleration	678	80.81
	fbeh	fbeh2	breaking	49	5.84
		fbeh3	accelerate	112	13.35
	sba	sba1	continue direction	679	80.93
		sba2	evasive behavior	160	19.07
		sbeh1	Constant acceleration	650	77.47
	sbeh	sbeh2	breaking	96	11.44
		sbeh3	accelerate	93	11.08
		fts1	[0,5]	145	17.28
Interaction Behavior	fts(m)	fts2	(5,15]	562	66.98
		fts3	(15,30]	127	15.14
		fts4	(30,+∞)	5	0.60
		vfs1	[0,4]	485	57.81
	vfs(m/s)	vfs2	(4,8]	255	30.39
		vfs3	(8,12]	98	11.68
		vfs4	(12,+16]	1	0.12
		fas1	[0,5]	717	85.46
	fas(m)	fas2	(5,10]	95	11.32
		fas3	(10,30]	27	3.22
		afs1	[0,10]	410	48.87
	afs(m/s)	afs2	(10,30]	332	39.57
		afs3	(30,60]	86	10.25
		afs4	(60,90]	11	1.31
		sig1	[0,10]	82	9.77
signal control	signal	sig2	(10,L-10]	698	83.19
		sig3	(L-10,L]	59	7.03
		s-type1	bicycle	234	27.89
other factor	s-type	s-type2	electric bicycle	605	72.11

- # Orginal Logit

$$y_i = j \qquad \text{if } \gamma_{j-1} < \gamma_i^* \leq \gamma_j \tag{4}$$

Where, $\tau = (\gamma_0, \gamma_1, \dots, \gamma_j, \dots, \gamma_J)$, A grading point indicating the severity of a conflict event. Here $(\lambda_0 < \lambda_1 < \cdots < \lambda_j < \cdots < \lambda_J, \lambda_0 = -\infty, \lambda_J = +\infty)$

$$y_i^* = BX_i^T + \varepsilon \tag{5}$$

Where, $X_i^T = (x_{i1}, x_{i2}, \dots, x_{ik}, \dots, x_{iK}; i = 1, \dots N; k = 1, \dots, K)$ is a vector of observations of factors influencing the severity of conflict events. $B = (\beta_0, \beta_1, \dots, \beta_k, \dots, \beta_K)$ is the parameters corresponding to influencing factor variables. The x_{ik} in X_i^T is the observed value of the $k-th$ influencing factor in the $i-th$ conflict event. N is the total number of accidents in the sample; K is the number of factors affecting each accident; ϵ_i is the random error term, which is the sum of other factors that are difficult to observe but impact the severity of the accident.

- The probability that the severity of the $i-th$ accident is y_j.

$$\begin{aligned} Pr(y_i = j \mid X_i, B, \Gamma) &= Pr(\gamma_{j-1} - X_i^T B < \epsilon_i \leq \gamma_j - X_i^T B) \\ &= F(\gamma_j - X_i^T B) - F(\gamma_{j-1} - X_i^T B) \end{aligned} \tag{6}$$

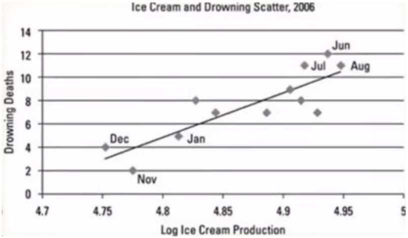
- Rate Ratio

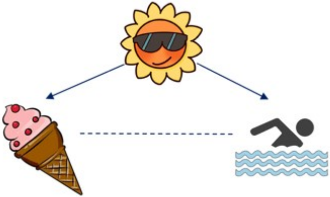
$$\Omega_j = \frac{Pr(y_i \leq j \mid X_i, B, \Gamma)}{1 - Pr(y_i \leq j \mid X_i, B, \Gamma)} = \frac{Pr(y_i \leq j \mid X_i, B, \Gamma)}{Pr(y_i > j \mid X_i, B, \Gamma)} = exp(\gamma_j - X_j^T B) \tag{7}$$

Causal Inference

- Define of Causal inference

➢ **classic example**





- **The basic three V-structures：**
  - chain $1 \rightarrow 2 \rightarrow 3$
  - fork $1 \leftarrow 2 \rightarrow 3$
  - collide $1 \rightarrow 2 \leftarrow 3$

Causal Inference

- Network learning methodology

➢ **network learning**

- Structural learning
- Parameter learning

- **Methodology based on conditional independence testing**

Feature Analysis:

✓ Strict following of causal inference theory and fully faithful to the dataset

✓ Requires a sufficient amount of rich data with a little noise

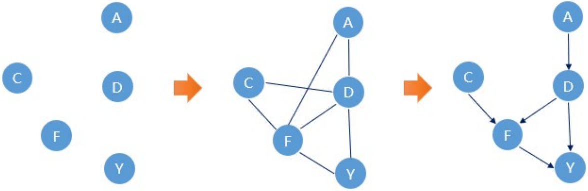
✓ Suitable for networks with a small number of nodes

- **Basic Processes**

① Based on the independence test Constructing a network skeleton

② Combining V-structures Make directional inferences

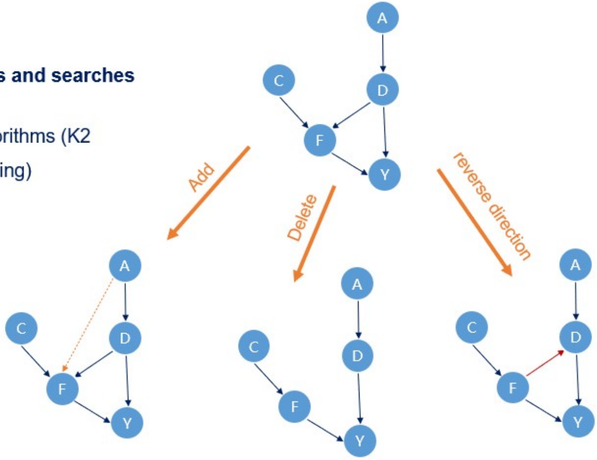
③ Adjustments based on expert experience



Causal Inference

- Network learning methodology

- **Methods based on ratings and searches**
  - Greedy search algorithms (K2 algorithm, hill-climbing)



Features：

- May fall into local optimization
- Highly influenced by initial values

Result

Result

Ordered Logit

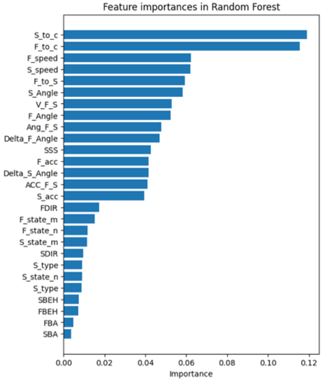
- Conflict Risk Ordered Logit Model ($p - values < 0.05$)

ttc-level	Coefficient	Std.err.	$P > \|z\|$	ttc-level	Coefficient	Std.err.	P¿—z—
fdir1	0.729	0.371	0.049	fbeh1	-0.164	0.223	0.462
fdir3	0.574	0.271	0.034	fbeh2	-0.581	0.340	0.088
sdir1	0.873	0.265	0.001	ss2	1.195	0.164	0.000
sdir3	1.184	0.534	0.027	ss3	0.454	0.636	0.475
fs2	0.606	0.159	0.000	smn1	0.267	0.168	0.112
fs3	0.733	0.368	0.046	stc1	5.178	0.710	0.000
fba1	-0.495	0.188	0.009	stc2	3.703	0.700	0.000
ftc2	-1.308	0.163	0.000	stc3	1.863	0.684	0.006
ftc3	-2.735	0.250	0.000	sig2	-0.042	0.240	0.863
ftc4	-2.123	0.609	0.000	sig3	1.297	0.373	0.001
sba1	-0.642	0.172	0.000	s-type2	0.609	0.167	0.000

Causal Inference

- Selecting Key Variables

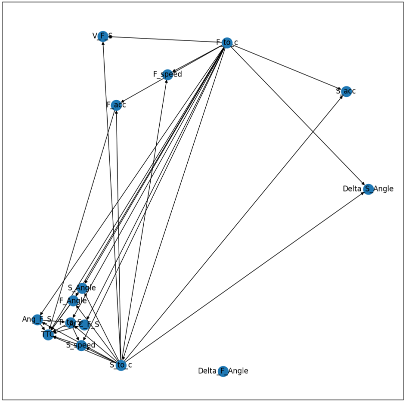
$$Normalized(x) = sign(x) \times \left(\frac{|x| - \min(|x|)}{\max(|x| - \min(|x|))} \right) \tag{8}$$



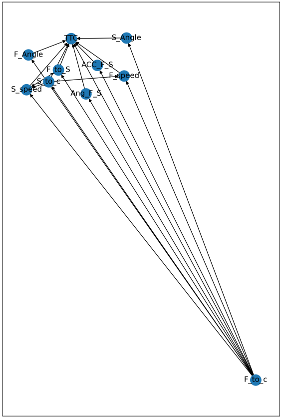
The importance of the variables is ranked based on the Random Forest

Causal Inference

- Network learning methodology



initial diagram



Adjustment based on experience

Causal Inference

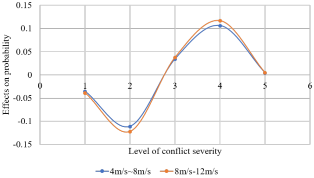
- chain of cause and effect

causal chain	Node1		Node2		Node3		Node4		Node5
1	F_to_c	——>	F_to_S	——>	TTC				
2	F_to_c	——>	S_speed	——>	TTC				
3	F_to_c	——>	F_angle	——>	TTC				
4	F_to_c	——>	S_to_c	——>	TTC				
5	F_to_c	——>	Ang_F_S	——>	TTC				
6	F_to_c	——>	ACC_F_S	——>	TTC				
7	F_to_c	——>	S_Angle	——>	TTC				
8	F_to_c	——>	F_angle	——>	S_speed	——>	TTC		
9	F_to_c	——>	F_to_S	——>	S_speed	——>	TTC		
10	F_to_c	——>	S_to_c	——>	F_angle	——>	TTC		
11	F_to_c	——>	S_to_c	——>	F_angle	——>	S_speed	——>	TTC

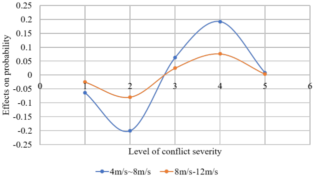
Discussion

Discussion

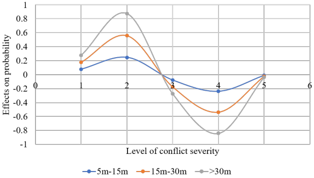
Marginal Effects of Significant Variables.



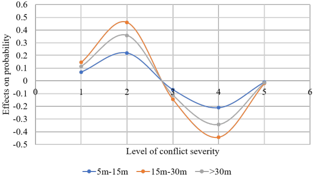
Marginal effects of the Speed with Non-motor vehicle



Marginal effects of Motor vehicle driving behavior



Marginal effects of the distances from non-motor vehicles to points of conflict



Marginal effects of the distances from motor vehicles to points of conflict

Conclusion

Conclusion

- The main variables affecting the severity of conflict between motorized and NMV are: Direction of vehicle travel, speed of vehicle, avoidance behavior of vehicle, distance from conflict point, environment of NMV, and signal time and type of NMV, with significance values below 0.05.
- The direction of travel of interacting vehicles at the intersection has a significant effect on the severity of collisions during the interaction, increasing the likelihood of serious conflict by more than 15% between a left-turn-right-turn interaction and a right-turn-right-turn interaction compared to a straight-right-turn interaction.
- The probability of serious conflict for interaction events that occurred within 10 seconds of the end of the green light phase was 20% higher than in the 10 seconds before the green light was activated.
  Complete parameter learning and compare model conclusions.

Thanks for your listening!
Any Questions?