

Investigating and Modeling Motorized and Non-Motorized Interaction Behavior in Center Area of Intersections

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Introduction

Motivation: The hybrid, heterogeneous driving behavior and the complex interaction behavior caused by the mixture of different vehicle types are some of the biggest challenges for automated vehicles and significant safety threats for vulnerable traffic participants in the center area of the intersection.

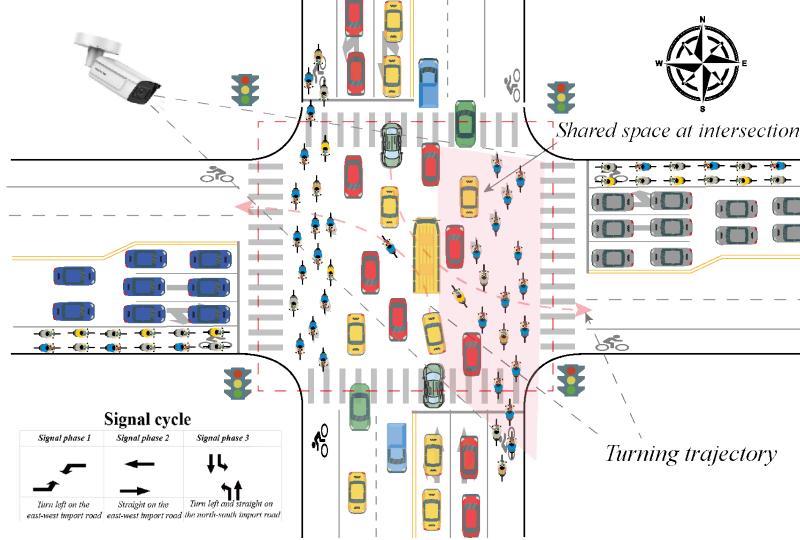


Fig. 1: The center area of the intersection.

- ► Challenges: a). Driving behavior in this area shows higher heterogeneity and non-stationarity; b). Conflict behavior during interaction is temporary and dynamic, which increases the difficulty of mechanism modeling.
- Research gaps:
 - Lacks attention to the evolution of conflict risk in interaction processes;
 - ► The impacts of signal control and the environment are ignored.

Summary

- We proposed a methodology for extracting high-resolution trajectories from the video and created a mixed traffic flow trajectory dataset.
- A framework was established for analyzing the evolution of conflict risk with the interaction between MVs and NMVs and made sure the factor related to the risk level significantly.
- The machines of interaction between MV and NMV are analyzed and the spatiotemporal variables are introduced to describe the interaction behavior.

Flowchart Obtaining high-precision trajectory data • Camera calibration Build a coordinate Recording video data transformation matrix Objective detection Labeling datasets Tracking trajectories Signal plan Intersection geometric training detection model Reconstructe the trajectory parameters **Driving Purpose** Getting dynamic interaction events Vehicle Movement Stat Calculate conflict risk inductor Traffic environme Extracte the interaction event chair Signal control Calculate the dynamic environment Other factor Discussion on

Fig. 2: The flowchart of methodology

Methodology

► Trajectory Data: (1)A new trajectory extraction software was built by integrating yolov7 and SFPF, a trajectory reconstruction algorithm previously developed by the team; (2)we obtained a complete set of 8160 trajectories with 185 interaction event chain from two interactions in Shanghai.

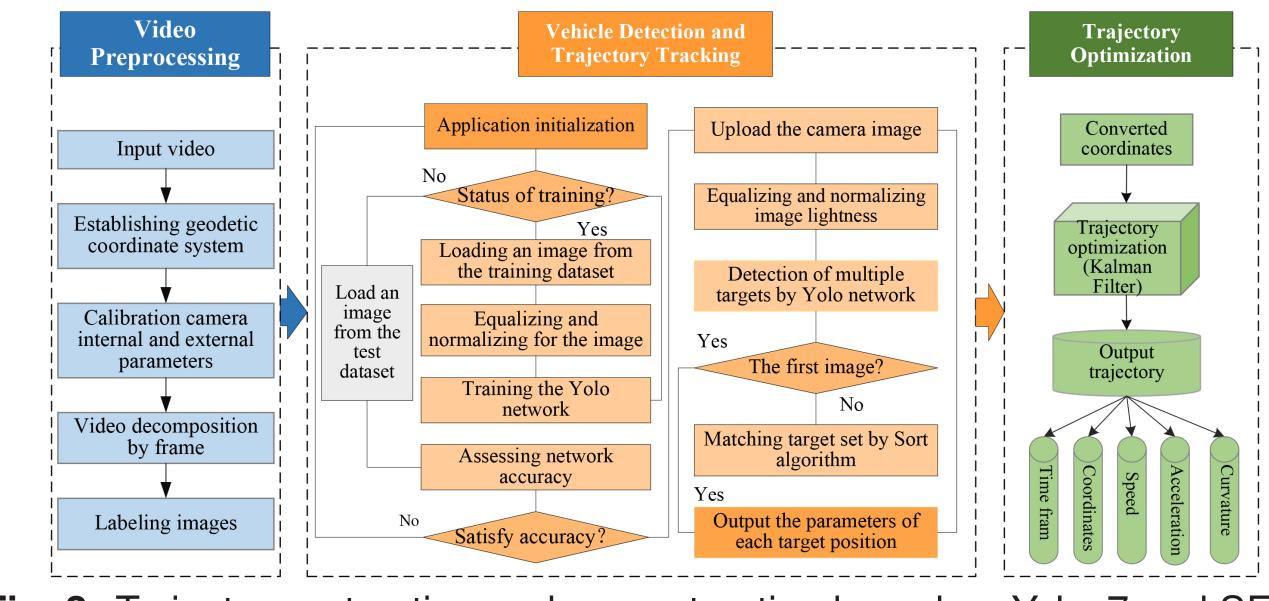


Fig. 3: Trajectory extraction and reconstruction based on Yolov7 and SFPF.

Extracting interaction event chain: Extracting the interaction process based on two dimensional TTC.

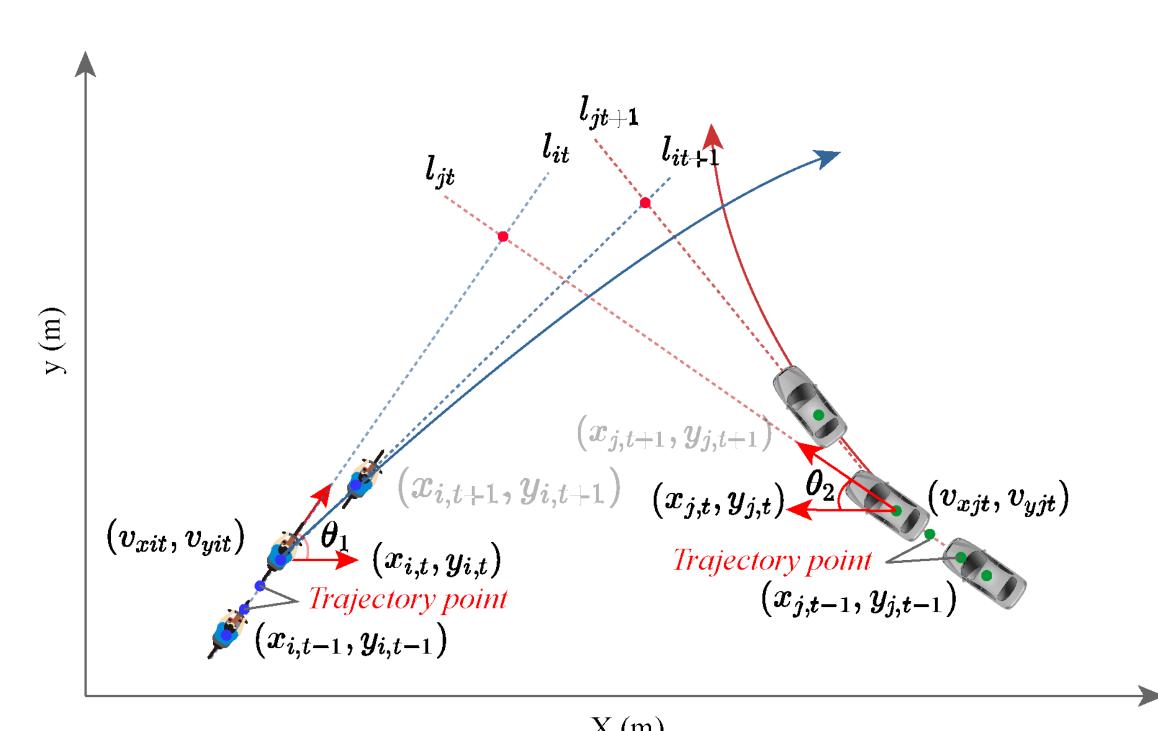


Fig. 4: The process of interaction between MVS and NMVs

- ▶ Defining interaction variables: We categorize the potential influencing factors affecting the risk of vehicular conflicts according to driving direction, motion states, interaction behavior, environment, vehicle type, and signal. Twenty variables variables related to the level of conflict risk were selected.
- Model: The Ordinal logit model is employed to analyze the relationship between risk level and the impact factors that were predefined.
 - continuous variable y_i^* into an observable ordered variable y to represent conflict severity, $y \in [-\infty, +\infty]$. $y_i = j$ if $\gamma_{j-1} < \gamma_i^* \le \gamma_j$
 - The general form of the model is shown in the fellow equation.

$$y_i^* = BX_i^T + \varepsilon$$

▶ The probability that the severity of the i - th accident fellow equation.

$$Pr(y_i = j \mid X_i, B, \Gamma) = Pr(\gamma_{j-1} - X_i^T B < \epsilon_i \le \gamma_j - X_i^T B)$$

= $F(\gamma_j - X_i^T B) - F(\gamma_{j-1} - X_i^T B)$

The coefficients β and the severity grading points τ of each influencing factor were estimated using maximum likelihood estimation.

Experiments & Results

Model results:

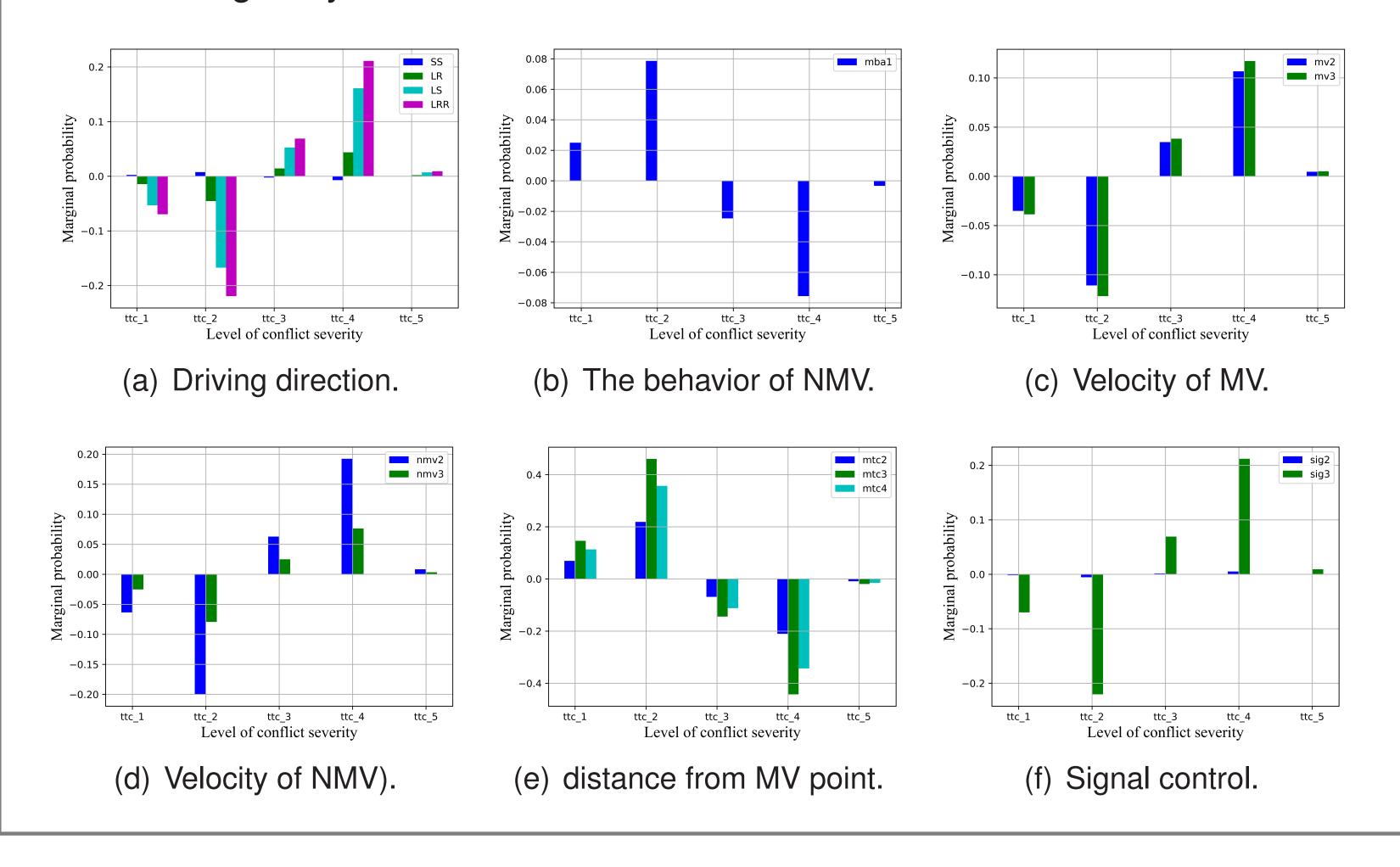
► Ten variables have a significant effect on conflict risk severity with a p-value less than 0.1.

Table 1: The significance variables from ordinal logistics Model (p < 0.05)

Variable	Coefficient	Std.err.	P > z	Variable	Coefficient	Std.err.	P > z
$mdir_1$	0.729	0.371	0.049	$ mbh_1$	-0.164	0.223	0.462
$mdir_3^-$	0.574	0.271	0.034	$\parallel mbh_2^-$	-0.581	0.340	0.088
$nmdir_1$	0.873	0.265	0.001	$ nmv_2^-$	1.195	0.164	0.000
$nmdir_3^-$	1.184	0.534	0.027	$ nmv_3^-$	0.454	0.636	0.475
mv_2	0.606	0.159	0.000	$ nmmn_1 $	0.267	0.168	0.112
mv_3^-	0.733	0.368	0.046	$ nmtc_1^{-} $	5.178	0.710	0.000
mba_1	-0.495	0.188	0.009	$ nmtc_2^{-}$	3.703	0.700	0.000
mtc_2	-1.308	0.163	0.000	$ nmtc_3^-$	1.863	0.684	0.006
mtc_3	-2.735	0.20	0.000	$\parallel sig_1$	-1.297	-3.48	0.001
mtc_4	-2.123	0.609	0.000	$\begin{vmatrix} sig_3 \end{vmatrix}$	-1.256	-4.06	0.000
nma_1	-0.642	0.172	0.000	$ nmt_2$	0.609	0.167	0.000
γ_4	8.032	0.839	·	_			

Marginal effects:

► We take the mean value of other variables and calculate the change in the probability of a different conflict risk level when the observed variable is changed by one unit.



Conclusion

- The main variables affecting the severity of conflict between MV and NMV are direction, speed, Evasive behavior, distance to conflict point, the number of MV surrounding NMV, signal time and type of NMV.
- ➤ 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 beginning of the green light.
- Significant variables related to interaction behavior show that the probability of a serious conflict decreases by 20% when the distance to conflict point is more than 15 meters, compared to a distance of less than 5 meters.

Shanghai-Mixed-Traffic-Flow-Trajectory

https://www.kaggle.com/datasets/zcyan2/mixed-traffic-trajectory-dataset-in-from-shanghai