Journal of Zhejiang University-SCIENCE A

Lateral risk prediction and influencing factor analysis of container trucks based on trajectory reconstruction data

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Cite this as: Zhihao ZHU, Hexuan LIU, Rongjun CHENG, 2025. Lateral risk prediction and influencing factor analysis of container trucks based on trajectory reconstruction data. *Journal of Zhejiang University-SCIENCE A*, 26(12):1211-1228. https://doi.org/10.1631/jzus.A2500331

Method framework

Using drones to collect natural driving trajectory data of container trucks, the trajectory of the raw data extracted by YOLOv8 is reconstructed, and a two-dimensional TTC index is developed to identify sideslip conflicts. Based on this, a machine learning model is used to predict whether different types of conflicts will occur, and SHAP theory is used to explain the influence of different factors on the conflict mechanism. Finally, feature ablation experiments are conducted to further improve the predictive performance of the model.

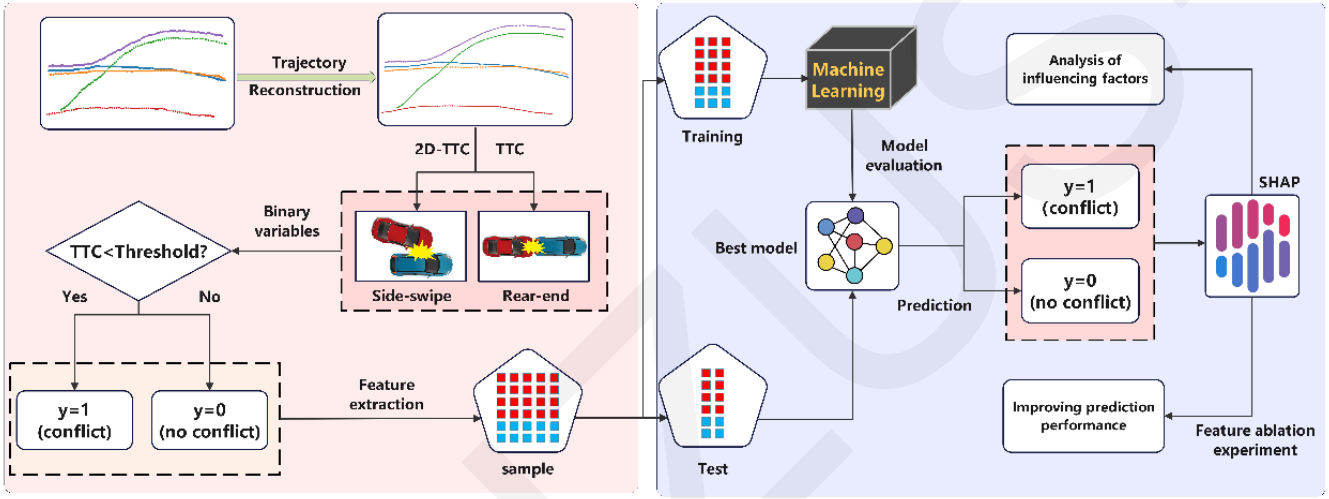


Fig. 1. Method framework.

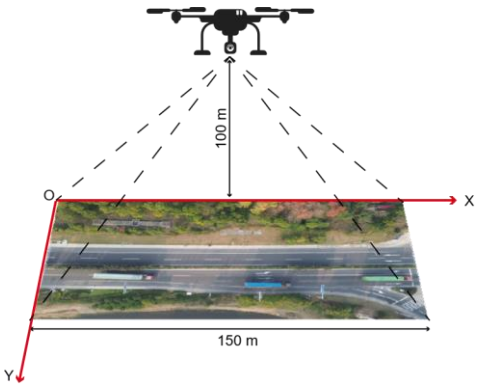


Fig. 2. Road section recorded by drone.

- **Step 1 data collection (Fig.2)**
- **Step 2 trajectory reconstruction**
- **Step 3 Conflict type identification**
- **Step 4 Analysis of influencing factors and model development**

Theoretical Derivation

This mainly includes the theory of trajectory reconstruction and two-dimensional TTC.

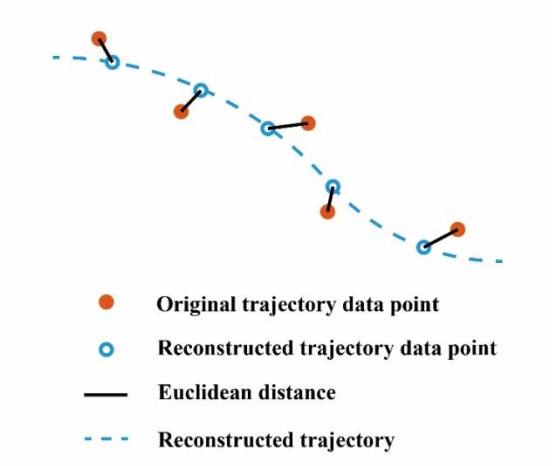


Fig. 3. Trajectory reconstruction principle.

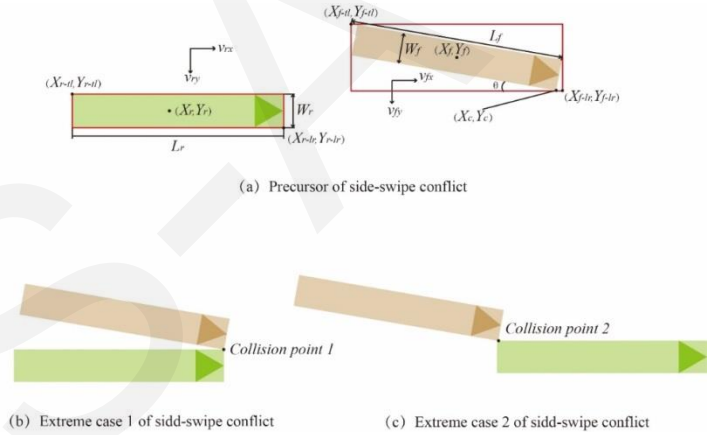


Fig. 4. Side-swipe conflict identification principle.

Optimization Objective : $\min C = \min \sqrt{\frac{1}{N}\sum_{i=1}^{N} D(L_i)}$

$$D(L_i) = \left(x_i - x_{orignal,i}\right)^2 + \left(y_i - y_{orignal,i}\right)^2$$

Constraints: $0 \le v \le v_{\max}$

$$a_{T\min} \le a_T \le a_{T\max}, a_{C\min} \le a_C \le a_{C\max}$$

$$-j_{\max} \le \frac{a(i+1)-a(i)}{\Delta t} \le j_{\max}$$

$$X_c = X_{f-lr} - W_f \sin\theta$$

$$Y_c = Y_{f-lr}$$

$$TTC_{x1} = \frac{X_c - X_{r-lr}}{v_{rx} - v_{fx}}$$

$$TTC_{x2} = \frac{X_c - X_{r-lr} + L_r}{v_{rx} - v_{fx}}$$

$$TTC_y = \frac{Y_{r-tl} - Y_c}{v_{fy} - v_{ry}}$$

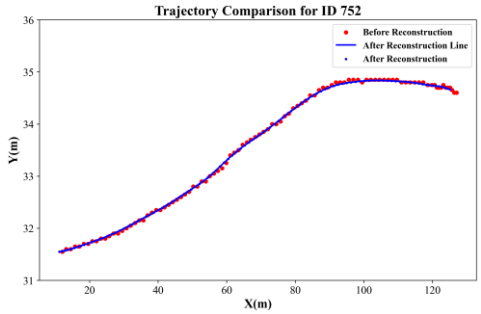
Judgment conditions $TTC_{x1} \le TTC_y \le TTC_{x2}$

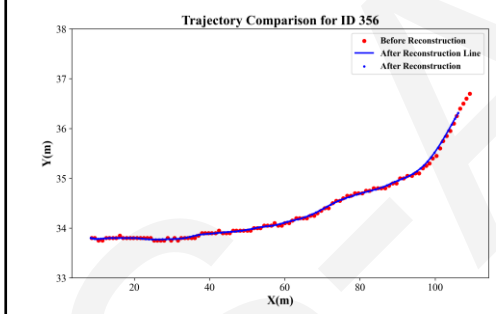
If the above criteria are met and the TTC value is less than the threshold, a conflict occurs.

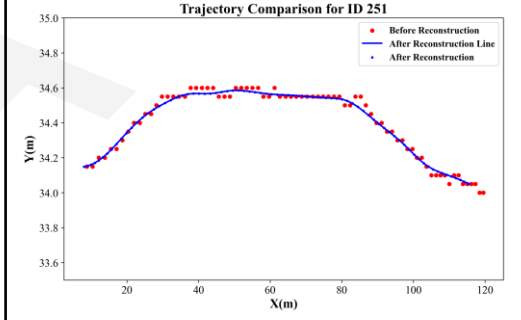
Trajectory reconstruction effect

Vehicle trajectory

straight and lane change

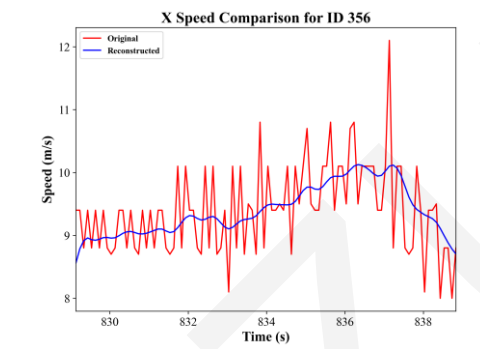


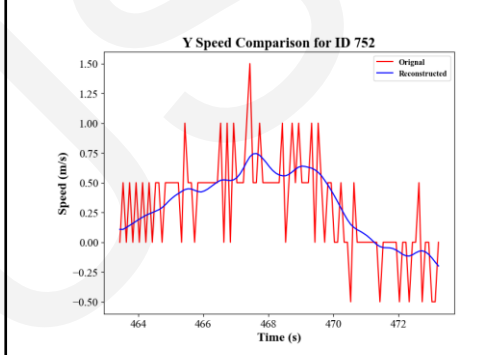


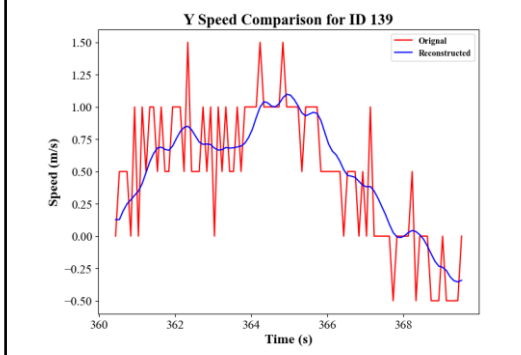


speed

longitudinal and lateral

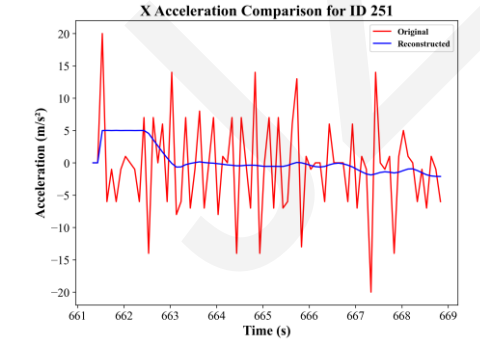


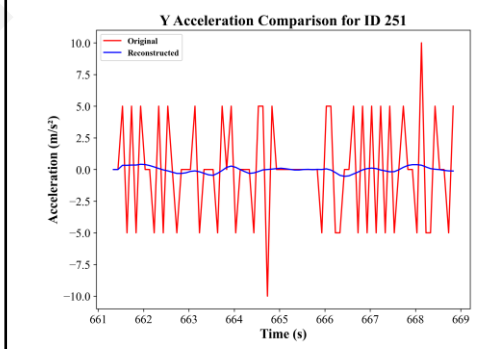


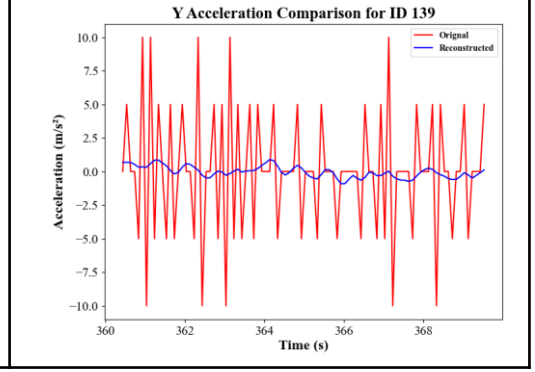


acceleration

longitudinal and lateral







Results Analysis and Model Improvement

This section includes an analysis of the influencing factors for two types of conflict and performance improvements of their predictive models

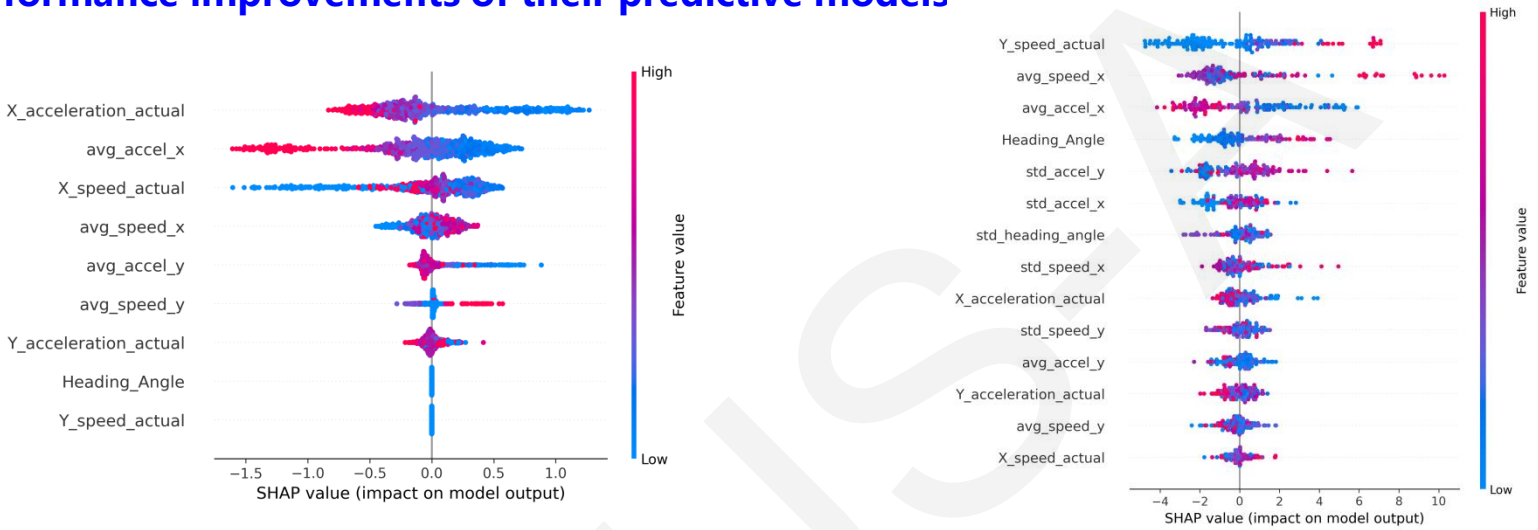


Fig. 5. Summary diagram of SHAP values of factors influencing rear-end conflict and side-swipe conflict.

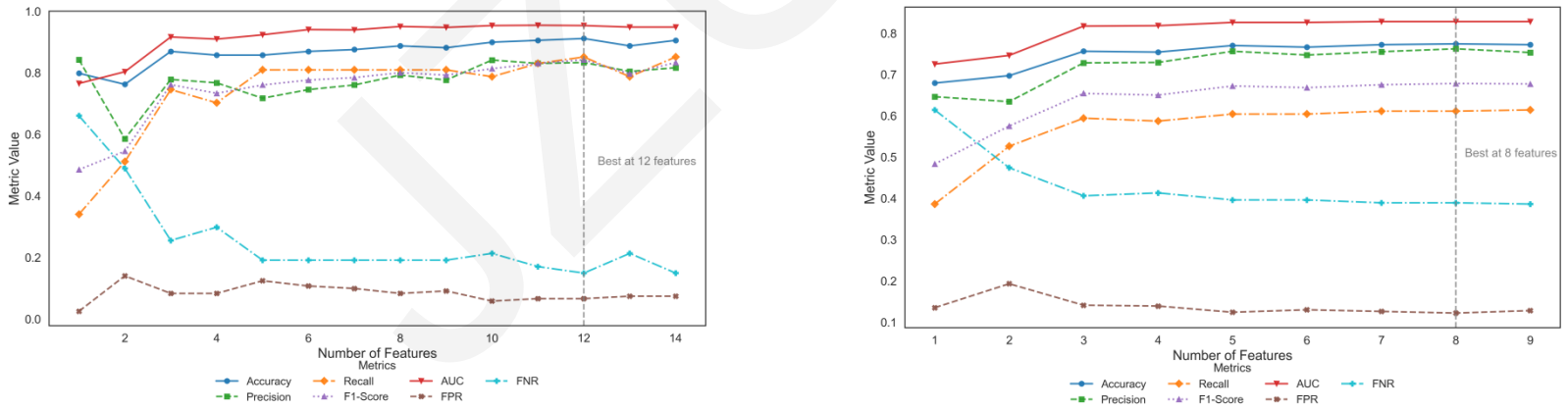


Fig. 6. Ablation experiments on features of rear-end conflict and side-swipe conflict prediction models.

Conclusions

- Compared with the original data, after trajectory reconstruction, the trajectory and its speed, acceleration and jerk become more reasonable, which is in line with the actual vehicle driving conditions. The video dataset shot by drones has the problem of data accuracy, and the trajectory reconstruction method solves this problem well.

- Considering the interaction of vehicles in two-dimensional space, the developed 2D-TTC can well identify side-swipe conflicts. Higher lateral speed and average longitudinal speed within 5 s are more likely to cause side-swipe conflicts, and lower average acceleration within 5 s is also more likely to cause conflicts. The GBDT model with 12 features was finally selected to achieve the best performance in identifying side-swipe conflicts, with an accuracy of 0.911 and AUC of 0.953.

- The most important features affecting rear-end conflicts are longitudinal acceleration and average acceleration within 5 s. When these two values are low, rear-end conflicts are more likely to occur. Finally, the XGBoost model with 8 features was selected, which achieved the best performance in identifying rear-end conflicts, with an accuracy of 0.774 and AUC of 0.828.