An integrated simulation framework to validate a traffic conflict prediction algorithm

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RSS Presentation

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The way forward

- Background
- Research problem
- Aim
- Data collection
- Methodology
- Results
- Discussion
- Conclusion

Background

94%

of traffic collisions are attributed to driver error → autonomy.

ADAS

systems are constantly being developed in intelligent vehicles to enhance safety, e.g., CAS, ACC, LDW, LKA.

Traffic Conflicts

Multiple surrogate safety measures and factors (e.g., speed variance) influencing them in real-time.

Conflict Detection Technique

Large, heterodox, imbalanced data start to emerge → require a suitable technique require testing and validation.

Research Problem

- Existing ADAS use only one SSM (TTC), based on a threshold value.

- Big, imbalanced, complex and highly disaggregated data (AI).

- Validation is challenging.

Data Collection

Example of Data collection

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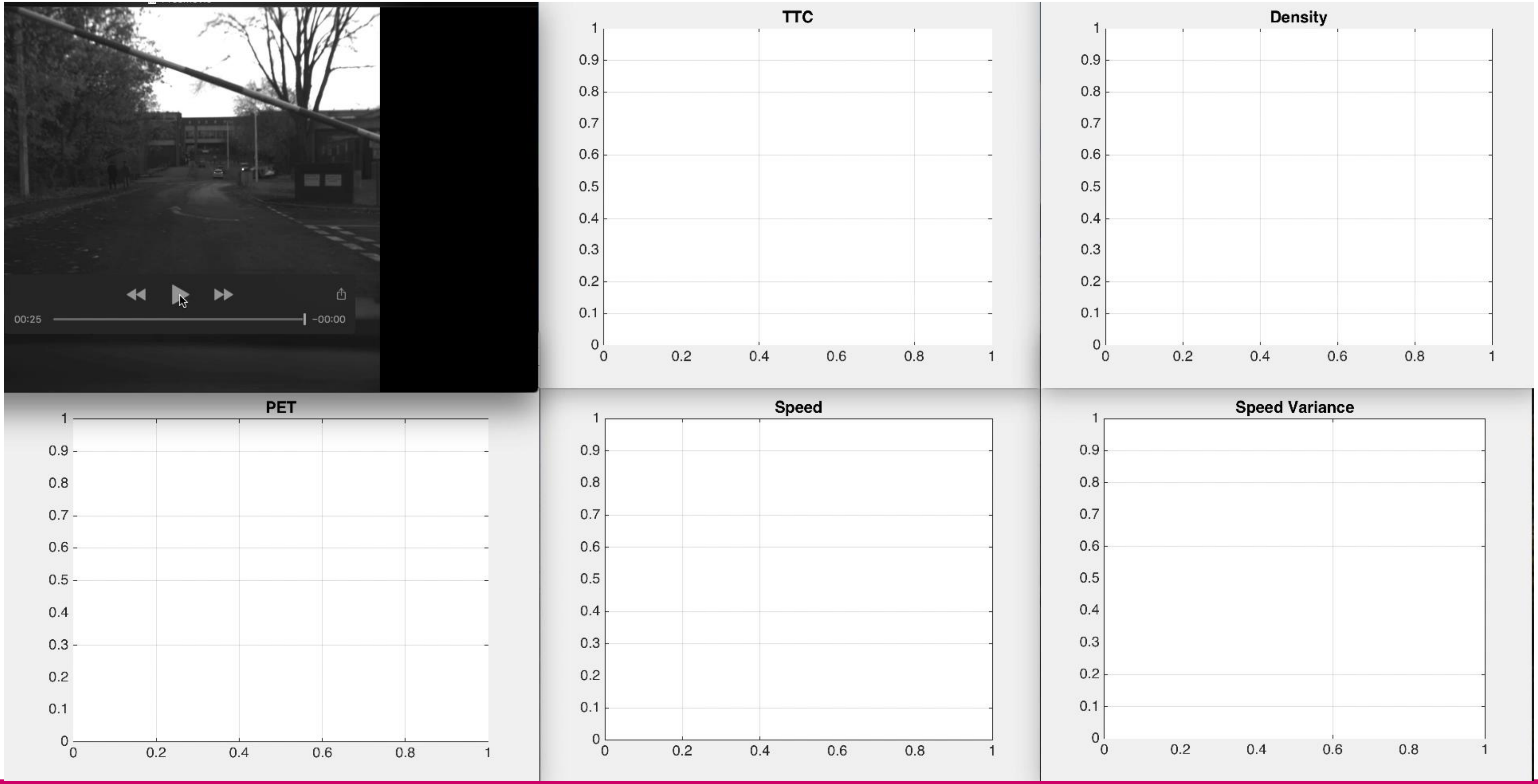

Methodology

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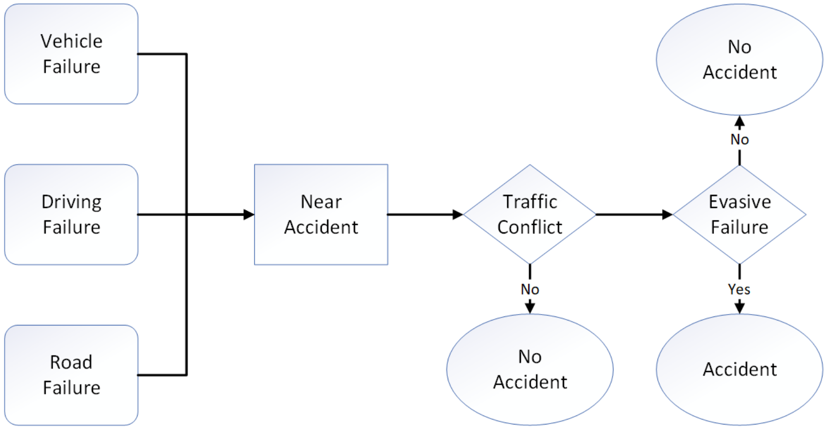
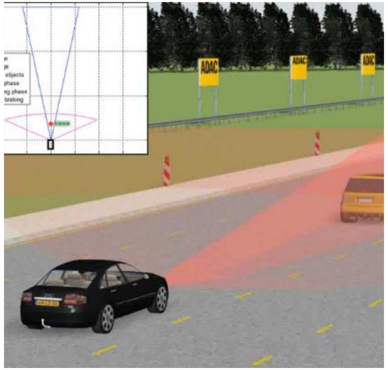
1. Traffic conflict identification

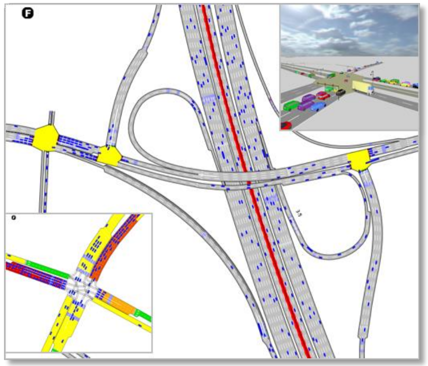
   - Generation of ground truth data



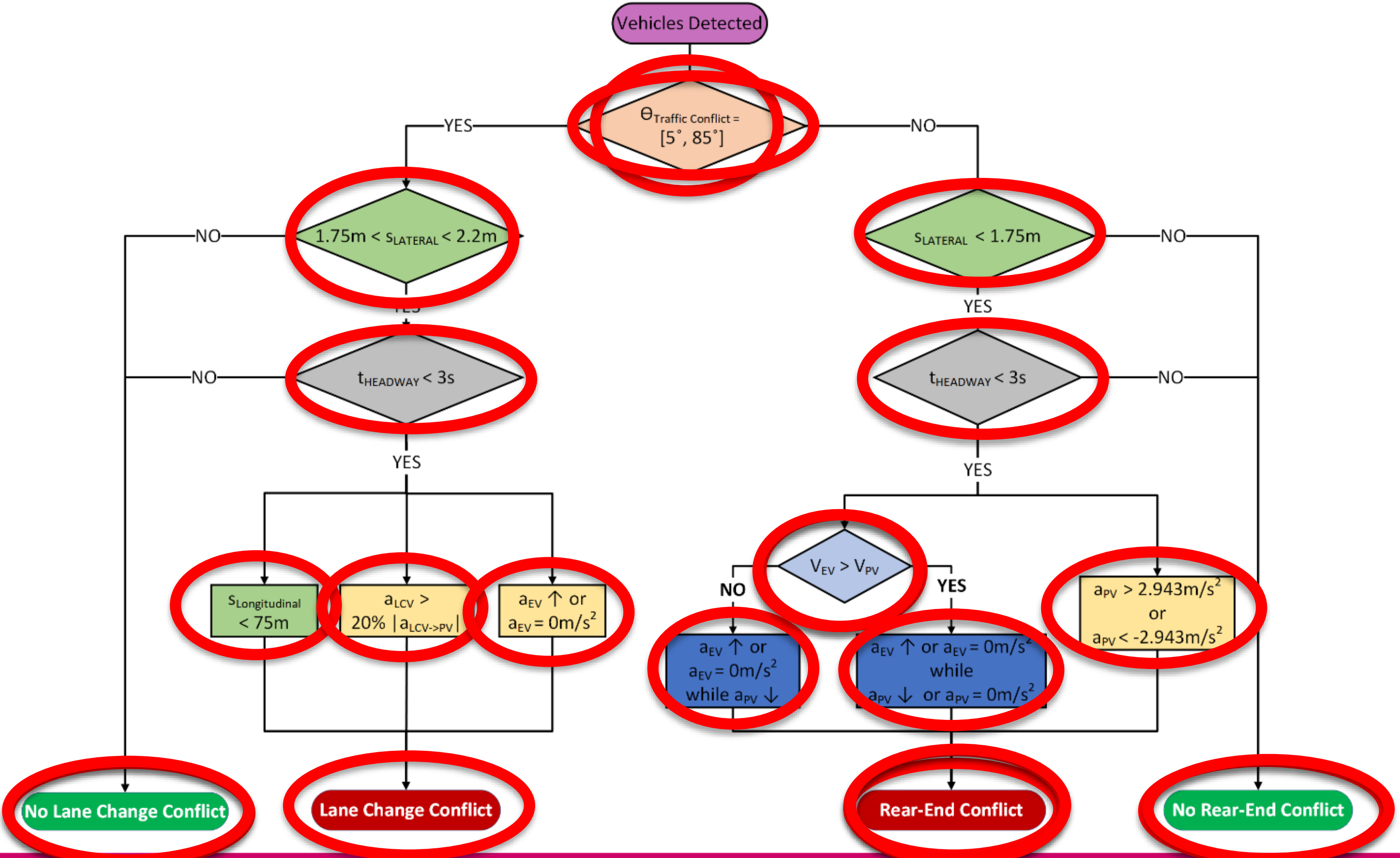
2. Traffic conflict model validation

   - Sub-microscopic simulation (PreScan)
   - Microscopic simulation (PTV Vissim)





Traffic conflict identification

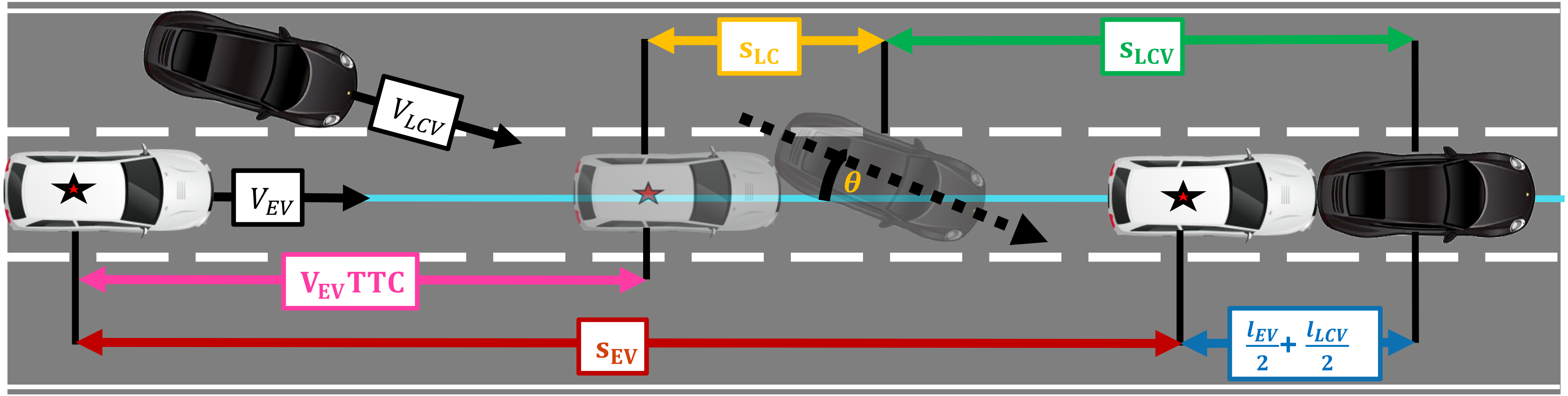


Lane Change Conflict identification – validation

$$\mathbf{s_{EV}} \leq \mathbf{V_{EV}TTC} + \mathbf{s_{LC}} + \mathbf{s_{LCV}} - \left(\frac{\mathbf{l_{LCV}} + \mathbf{l_{EV}}}{\mathbf{2}}\right)$$

$$\mathbf{V_{EV}(TTC + t_{LC})} - \frac{\mathbf{a}}{\mathbf{2}}\left(\mathbf{TTC} + \frac{\mathbf{l_{LCV}}}{\mathbf{V_{LCV}}} - \right)^{2} \leq \mathbf{V_{EV}TTC} + \frac{\mathbf{w_{LCV}}}{\mathbf{2sin\theta}} + \frac{\mathbf{w_{EV}}}{\mathbf{2tan\theta}} + \frac{\mathbf{l_{LCV}(1 + cos\,\theta)}}{\mathbf{2}} - \left(\frac{\mathbf{l_{LCV}} + \mathbf{l_{EV}}}{\mathbf{2}}\right)$$

where $\mathbf{TTC}$-time to collision, $\mathbf{t_{LC}}$ - time to LC, $\mathbf{l}$ and $\mathbf{w}$ are the length and width of the vehicle

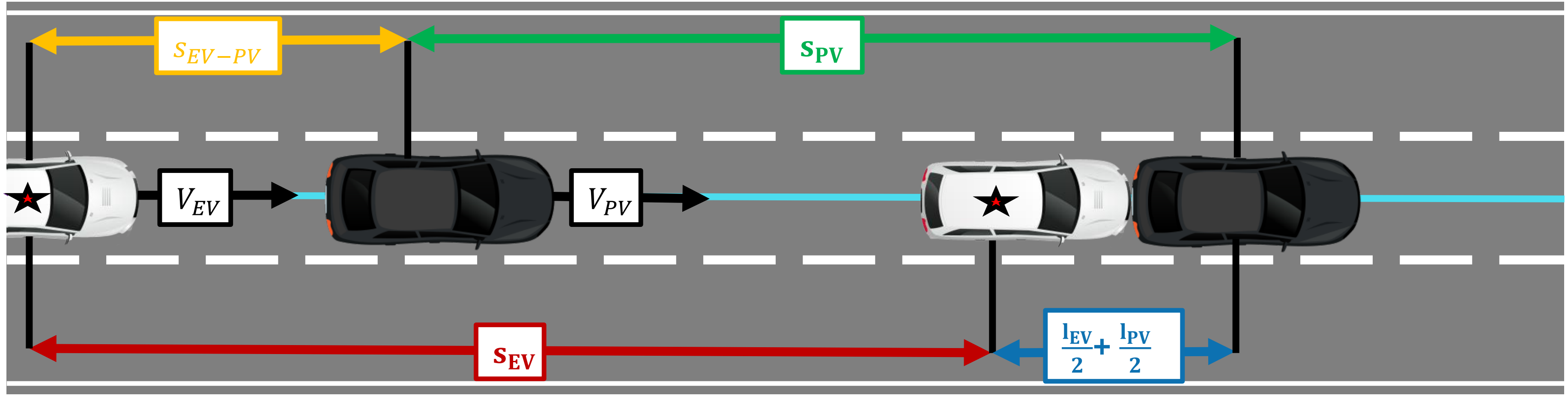


Rear-End Conflict identification - validation

$$\mathbf{s_{EV}} \leq \mathbf{s_{EV-PV}} + \mathbf{s_{PV}} - \left(\frac{\mathbf{l_{EV}} + \mathbf{l_{PV}}}{2}\right)$$

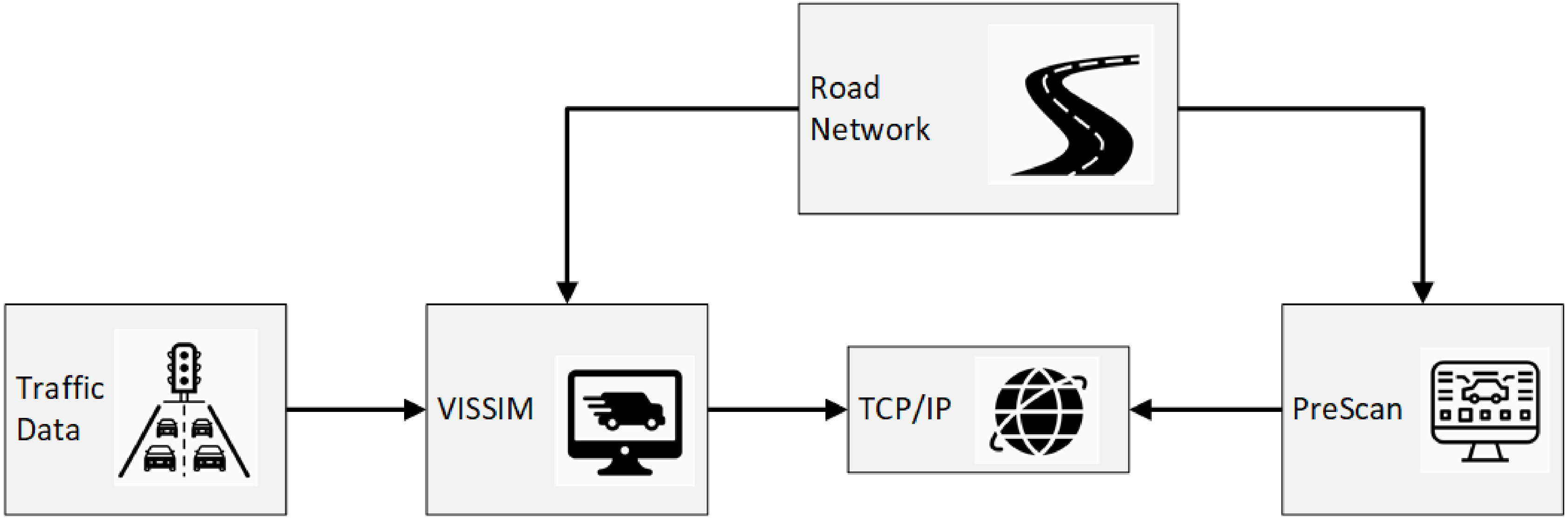
$$\mathbf{V_{EV}X} + \frac{\mathbf{V_{EV}^2} - \mathbf{V_{PV}^2}}{2\mathbf{a_{EV}}} \leq \mathbf{V_{EV}TTC} + \left(\frac{\mathbf{l_{EV}} + \mathbf{l_{PV}}}{2}\right) - \mathbf{V_{PV}TTC} + \frac{\mathbf{V_{PV}(V_{EV} - V_{PV})}}{\mathbf{a_{EV}}} - \left(\frac{\mathbf{l_{EV}} + \mathbf{l_{PV}}}{2}\right)$$

where **TTC**-time to collision, **l** is the length of the vehicle



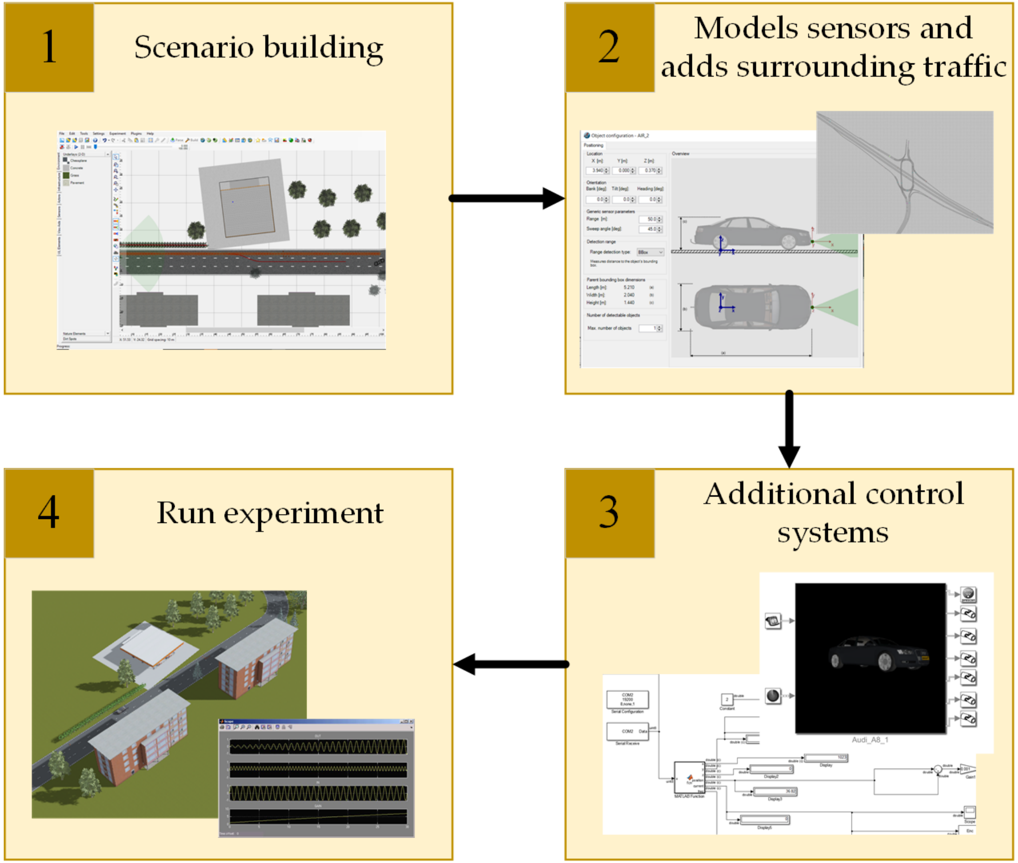
Traffic conflict model validation

Simulation Framework

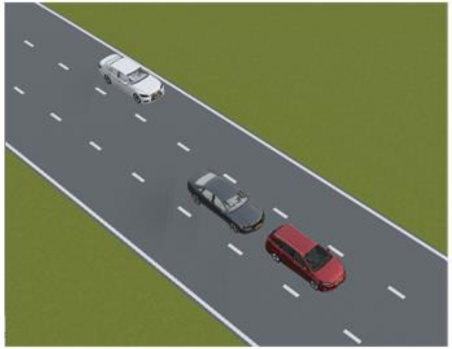


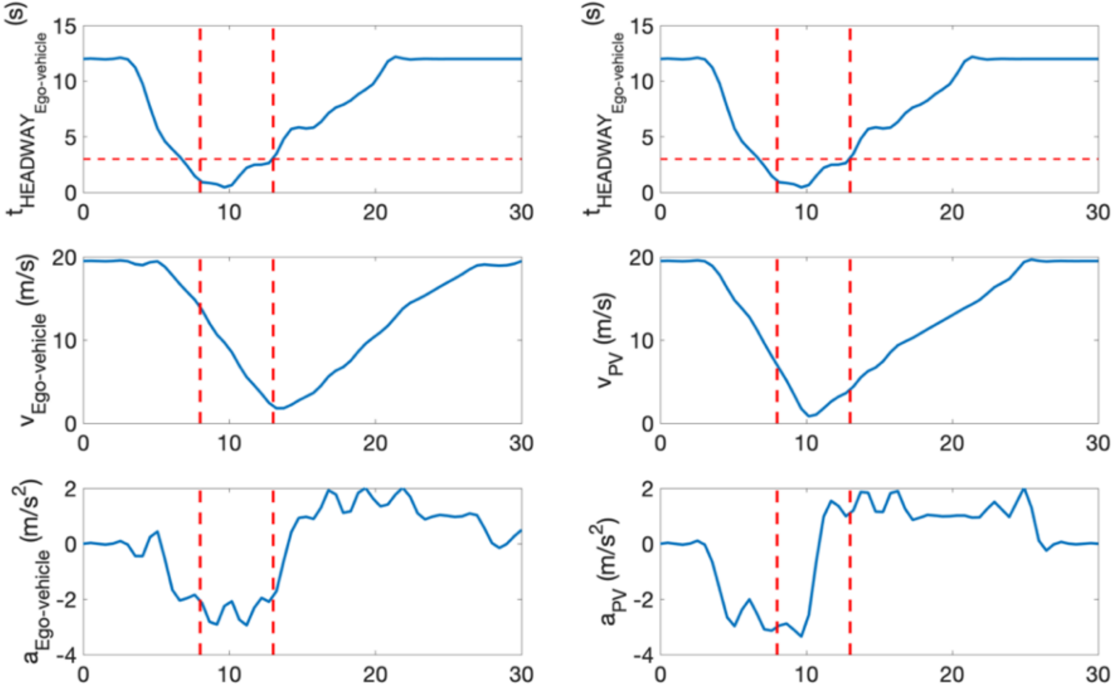
Integrated Conflict Validation framework

A comprehensive integrated platform is developed using a microscopic simulator VISSIM and a sub-microscopic simulator PreScan to validate models.

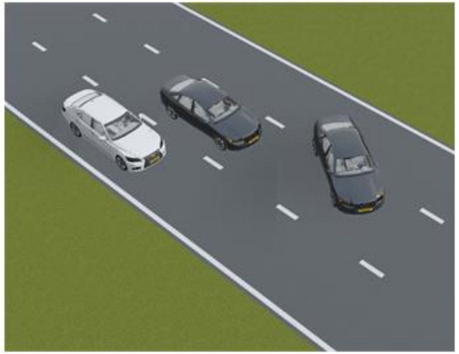


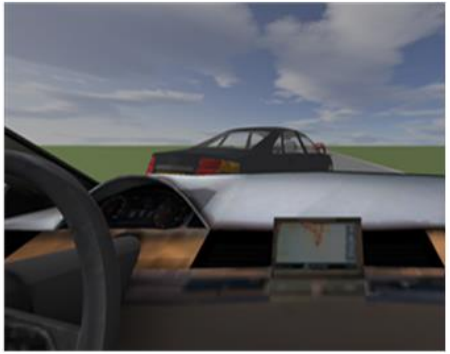
Example 1: Rear-End conflict

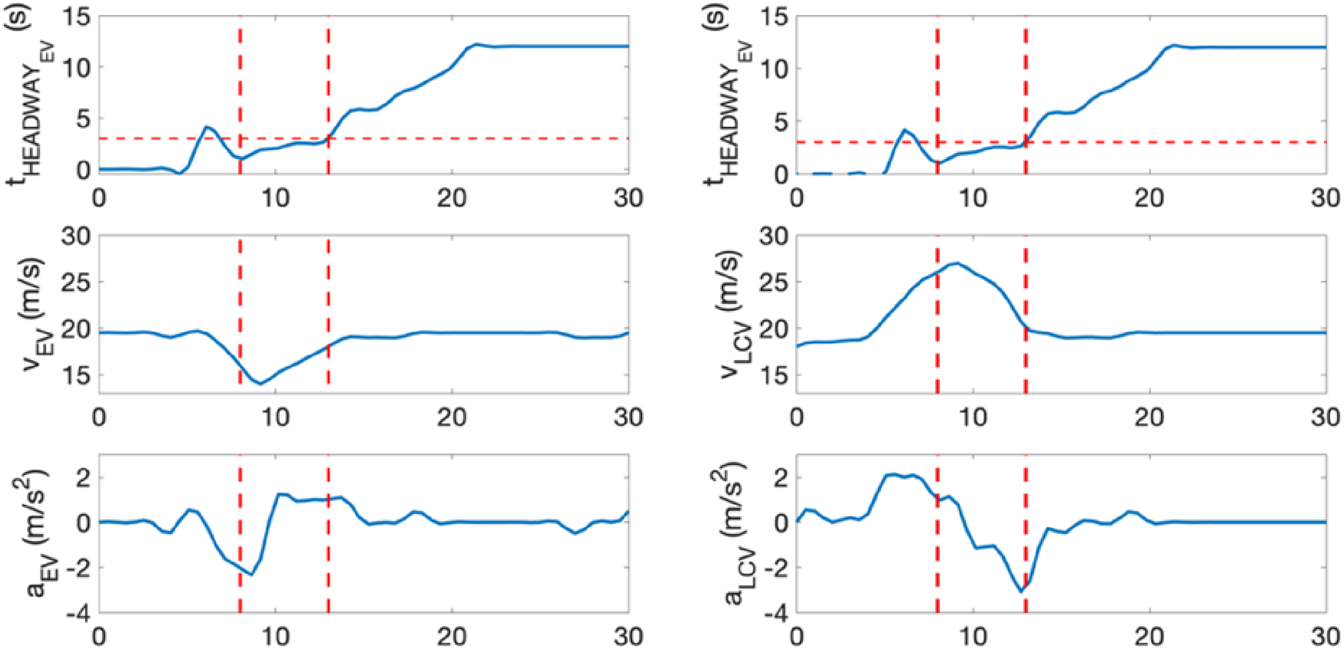




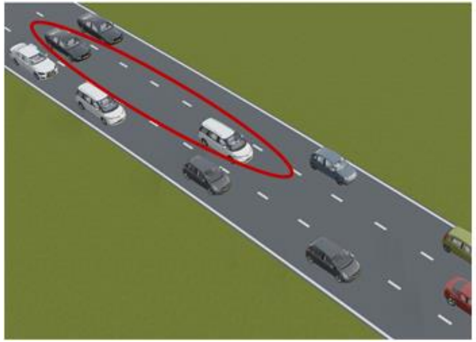
Lane change conflict

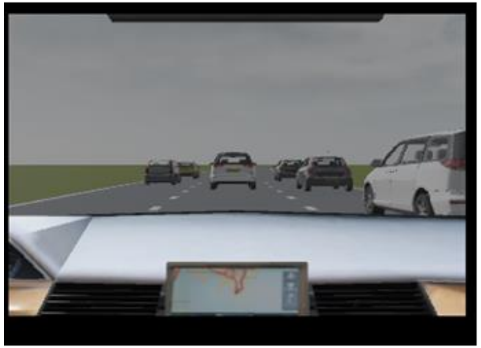


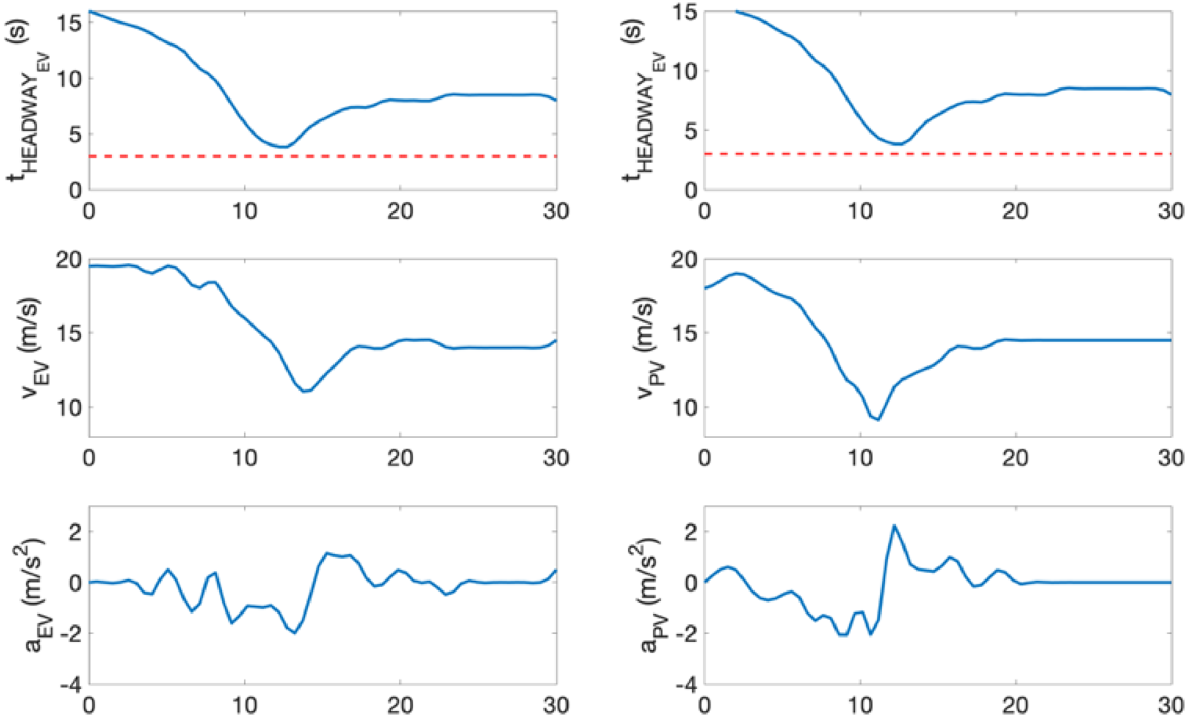




No conflict

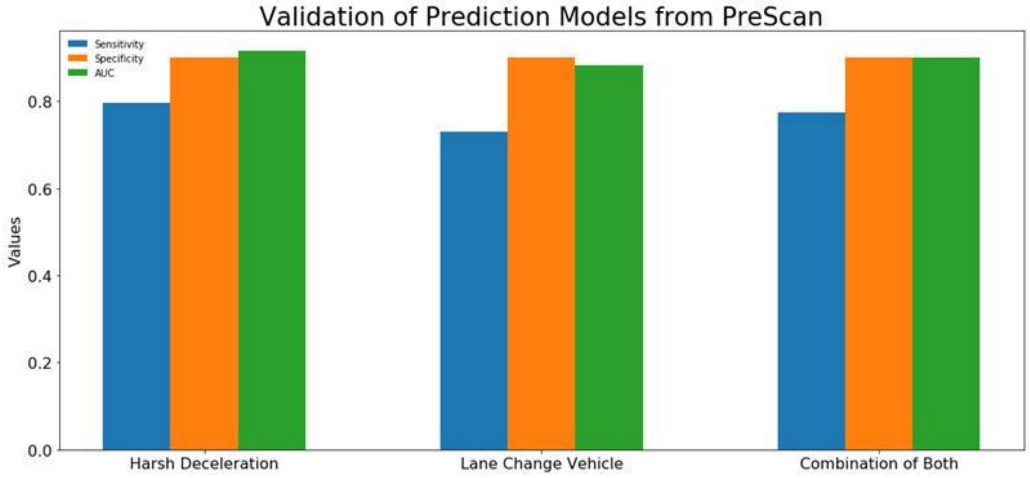


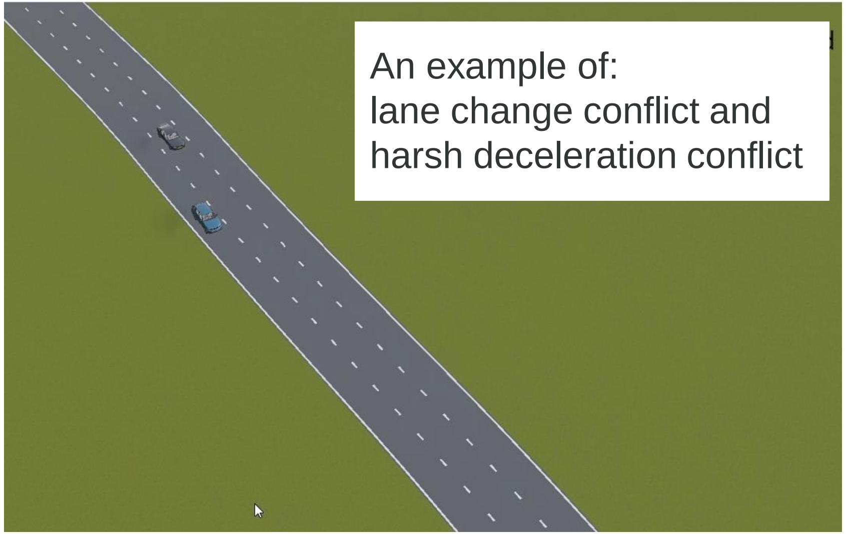




Overall Results (1)

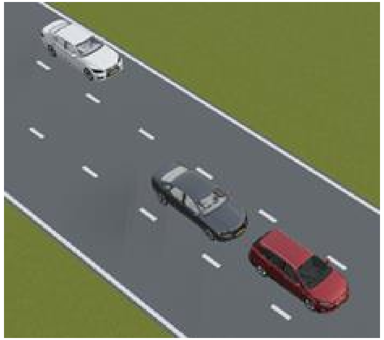
Validation of traffic conflict prediction model based on 3 scenarios at 10% FAR

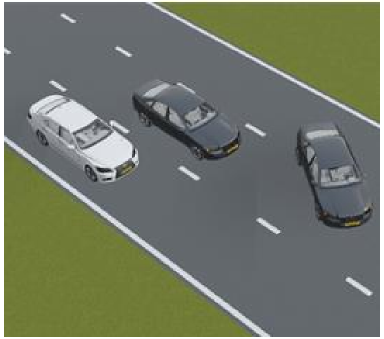




Overall Results (2)

(i) Scenario 1 – Preceding Vehicle performs harsh deceleration			
Average Sensitivity	FAR	Average Accuracy	Average AUC value
0.797	10.0%	0.844	0.916
0.843	20.0%	0.783	
(ii) Scenario 2 – LCV cuts in before Ego-vehicle			
Average Sensitivity	FAR	Average Accuracy	Average AUC value
0.730	10.0%	0.819	0.883
0.785	20.0%	0.764	
(iii) Scenario 3 – Combination of both scenarios			
Average Sensitivity	FAR	Average Accuracy	Average AUC value
0.774	10.0%	0.839	0.901
0.812	20.0%	0.782	





Discussion

Model has a higher prediction accuracy

Results show that AUC values are also better than previous work

The methodology is transferable; model capable of classifying and predicting traffic conflicts based on a novel data set.

Potential to significantly improve the performance of existing ADAS; could also apply to CAVS & AVs for real-time conflict detection

Conclusions

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1. Testing and validating the developed algorithms is key to prove their effectiveness.

2. •Framework consists of a submicroscopic simulator, a microscopic traffic simulation to simulate based on real-time data.

3. Results from the integrated simulation framework - 80% of rear-end conflicts and 73% of lane change conflicts were predicted by algorithm for a 10% false alarm rate.

4. Overall – Despite that the algorithm was not trained using the virtual data, the sensitivity is high. Used in ADAS, AVs, CAVs to mitigate the risk of traffic collisions

Thank you!

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