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A generalised data-driven framework for conflict detection in autonomous driving

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Introduction

Traffic conflict is one of the most comprehensive Surrogate Safety Measures (SSM) to evaluate accident risk. This is widely recognised not only in the traffic safety community, but also in the emerging fields such as driving assistance and autonomous driving.

Over the past decades, many indicators of traffic conflicts have been proposed for different types of interactions. For example, Time-To-Collision (TTC) and Deceleration Rate to Avoid Collision (DRAC), along with their variants, primarily address rear-end conflicts; Time advantage (or predicted Post-Encroachment-Time, PET) is specifically used for path-crossing conflicts; in addition, composite indices are designed by integrating multiple indicators to deal with more complicated conflicts such as during lane changing.

The diverse indicators are pivotal in identifying various types of traffic conflicts and potential accidents. However, in the context of autonomous driving, this variety presents significant challenges as traffic conditions and the interactions with other road users evolve continuously. For instance, a TTC of 3 seconds could be dangerous for vehicles rushing on highways, but arguably not for vehicles making a cooperative lane-change, nor for vehicles decelerating to approach an urban intersection. A 2-second PET could be accident-prone for cars crossing their paths at an intersection, but is commonly observed for bicycles.

In this study, we will present a new framework to detect varying conflicts in different traffic conditions and interaction scenarios. The framework adopts a data-driven approach and can be generally applied to all categories of road users. In practice, this study can contribute to standardised risk evaluation and decision-making for safer autonomous driving. In theory, by identifying potential accidents across evolving conditions, we believe the framework helps reveal the invariance over changes of traffic conflicts.

Research methodology

The framework proposed in this study does not cover kinetic energy-based surrogates that are used for crash severity estimation. Concerning the proximity-based conflicts only, all of the existing indicators are designed to measure the spatial-temporal closeness between road users under different considerations of traffic conditions and vehicle kinematics. Under the same conditions, the closer the proximity between the approaching road users, the less safe they are. When their proximity is too small to safely interact, a conflict emerges.

Following the same logic, we use two assumptions in our framework. First, given the same interaction context, the closer the interacting vehicles, the less safe they are and the higher the risk of a potential collision. Second, given the same interaction context, conflicts (i.e., unsafe interactions) are extreme events in extremely close proximity compared to safe interactions. Typically, the extreme value theory has been investigated by seeing crashes as the extreme events of conflicts. Here we take a step back and see conflicts as the extreme events of safe interactions.

The task of conflict detection can be generally formulated as estimating the probability of a conflict c, as shown in Equation (1),

$$p(c|s, X), \tag{1}$$

where the estimation is conditioned on s, denoting the proximity between interacting road users, and X, which encompasses the interaction information that can include but not limited to vehicle movements, traffic states, and road layouts.

We separate the conflict detection task into three sub-tasks as the conditional probabilities in Equation (2). Each of the sub-tasks aims to address a challenge in current conflict detection.

$$p(c|s, X) = p(c|s, \mu, \sigma)p(\mu, \sigma|\boldsymbol{\theta})p(\boldsymbol{\theta}|X). \tag{2}$$

The first sub-task $p(\boldsymbol{\theta}|X)$ is representation learning of interaction context $\boldsymbol{\theta}$ compressed from data X. Under a certain interaction context θ, the second sub-task $p(\mu, \sigma|\theta)$ learns the proximity distribution of safe interactions, as characterised by μ and σ. Then the third sub-task estimates conflict probability $p(c|s, \mu, \sigma)$ utilising extreme value theory. With μ and σ in the interaction context θ, we derive the distribution of extreme proximity, based on which we can estimate the probability of extreme events, i.e., conflicts, at different levels of extremity.

Discussion and conclusions

This framework has many advantages thanks to its flexibility. Using neural networks, each sub-task in this framework can be modelled in a data-driven manner and include almost all the information one can collect to describe an interaction between road users. This can go beyond vehicle movements, including road layouts, weather, drivers' individual characteristics, etc. It needs to note, however, that the more information gets involved, the more diverse data are needed to train an effective model.

Any conflict indicator based on proximity, whether existing or not yet, can be considered as a specific case within this framework. Take TTC as an example, the relative speed between vehicles is the interaction context $\boldsymbol{\theta}$; the net distance between vehicles is the proximity s. Using PET as another example, θ can be the requirement of crossing paths; s is the time interval (temporal proximity) between a vehicle leaves the conflict area and another vehicle enters the same area. Then the conflict determination for both TTC and PET is based on critical thresholds. Therefore, this generalised framework ensures that it performs at least as well as the indicator that is specifically designed for a type of conflict.