Reachability-Based Confidence-Aware Probabilistic Collision Detection in Highway Driving

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Autonomous vehicles (AVs) are expected to significantly benefit future mobility, while one of the prerequisites for enabling AVs publicly available is to ensure autonomous driving safety [1]. Highways are structured environments designed for vehicles to drive at a consistently high speed for efficient road trips, and are the first applications of Level 1 and Level 2 automated vehicles. In the transition from human-driven and lower-level automated vehicles to high-level AVs, it is essential to address driving safety on highways both for conventional vehicles and AVs. To identify driving risk and potential vehicle crashes, extensive research on risk assessment and collision detection has been conducted [2, 3]. To accurately detect potential vehicle collisions, reachability-based formal approaches have been developed [4], since they can mathematically check whether the behavior of a system, satisfies given safety requirements.

Reachability analysis (RA) has been widely employed to formally verify driving safety [5, 6]. RA computes a complete set of states that an agent (e.g. a vehicle) can reach given an initial condition within a certain time interval [7]. Based on RA, a safety verification thus can be performed by propagating all possible reachable space of the AV and other traffic participants on the road. In doing so, safety is ensured if such forward reachable set (FRS) of the automated vehicle does not intersect that of other traffic participants during the propagation period. In line with such a definition, FRS can formally verify safety between road users, but easily lead to over-conservative results because the state propagation is feedforward and ignore traffic participant interactions (i.e., vehicles react to the surrounding environment and adjust the control output) [7].

Alternatively, RA can be conducted in a closed-loop manner [8]. Given a target set representing a set of undesirable states (e.g., collision states between two vehicles) and worst-case disturbances, we define the backward reachable set (BRS) as the set of states that could lead to being in the target set during a certain time horizon. Specifically, BRS is the state set in which a control strategy does not exist to prevent the AV from the target set under worst-case disturbances. An unsafe area thus can be directly identified by BRS with initial vehicle states. Note that one can compute BRS offline in advance, and then use the cached BRS in real-time. Although BRS considers control reactions from the AV and is less conservative compared to FRS, BRS still suffers from over-conservatism due to the worst-disturbance closed-loop reactions.

We aim to use the RA for driving risk evaluation and potential collision detection. However, both these two RA approaches suffer from over-conservatism. To reduce the over-conservative nature of forward reachability, the time horizon for FRS is typically kept small and is recomputed frequently. Although BRS incorporates a closed-loop feedback to consider the worst disturbance from the surrounding vehicle, general interactions between vehicles are not a pursuit-evasion [9]. It is reasonable to consider a more realistic situation: *the interactions are not adversarial, but leading to crashes is still possible.*

In this work, we integrate the two RA approaches, and propose a collision detection framework to evaluate highway driving risk in Figure 1. The BRS is firstly computed based on Hamilton–Jacobi–Isaacs (HJI) partial differential equation (PDE) [8]; if the relative positions of vehicles are identified unsafe by BRS, a warning is provided to the ego vehicle, and a stochastic FRS considering surrounding vehicle manoeuvring modes is established to calculate a collision probability. Here the stochastic FRS shares the same reachable states as FRS. In addition, each state of a stochastic FRS has an estimated probability. It is ideal to directly use a stochastic BRS for collision detection, while the computation of a stochastic BRS is not readily viable due to the closed-loop form of BRS.

Based on the stochastic FRS, a collision probability between two vehicles can be calculated by summing up state probabilities where two vehicles spatially overlap. If the obtained collision probability is above a pre-defined threshold, the ego vehicle has to execute an emergency brake or swerve to avoid crashes with the surrounding vehicle. The proposed framework benefits from both BRS and FRS: the driving safety could be theoretically ensured when the relative vehicle positions are out of the unsafe area identified by BRS; otherwise the framework provides a collision probability based on a developed stochastic FRS.

Stochastic FRS has been constructed in different approaches for risk assessment and collision detection [10,

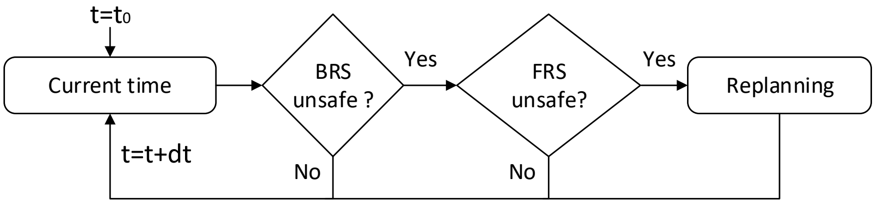

Figure 1: Brief diagram of the integrated collision detection framework.

11]. Heuristic rules [10] and action-state values [11] are employed to predict agent accelerations at each time step, and then the agent states with probability distributions are propagated for several future time steps accordingly. However, these methods propagate states only with the current state, while the agent state can be more accurately predicted using both current and historical information [12]. To realize this, we aim to develop a long-short term memory (LSTM) model for multi-maneuver acceleration prediction on highways. The proposed model has two stages for maneuver prediction (i.e., lane-keeping, turning-left/-right on highways) and acceleration prediction respectively, and the model input features are also selected differently at each stage.

By leveraging the LSTM prediction model [13], the accuracy of the stochastic FRS-based driving collision detection would largely depend on the model performance. This is because the applied prediction model cannot always be accurate, especially when vehicles move unexpectedly. To address this issue, we incorporate a confidence-aware belief vector to generate a group of predicted acceleration distributions, which can dynamically adjust the degree of confidence inferred from current prediction accuracy [11]. The confidence-aware belief vector could result in a concentrated stochastic FRS when the LSTM model has higher prediction accuracy, and lead to a more spread stochastic FRS when vehicles move unexpectedly.

Extensive experiments have been conducted to verify the proposed approach. We first introduce the employed naturalistic highway driving dataset highD [14], and experimental setup for the prediction model training/testing and the BRS/FRS computation. Then we test and validate the proposed prediction model performance, reachability-based state prediction and collision estimation, and the integrated collision detection framework. We have shown infusing confidence belief can indeed effectively improve the prediction accuracy, leading to more agile collision detection results. The integrated framework has also been tested in both risky and non-risky events. Future work could employ the proposed risk assessment framework on an actual vehicle.

The main contributions in this work are: Firstly, we propose a multi-modal acceleration prediction model for surrounding vehicles, and establish the stochastic FRS for each surrounding vehicle by leveraging the proposed acceleration predictor [15]. Furthermore, we incorporate confidence awareness to generate a group of predicted acceleration distributions, and dynamically update the degree of confidence, leading to a more accurate stochastic FRS and more agile collision detection results. Secondly, an integrated probabilistic collision detection framework including both BRS and stochastic FRS is proposed to evaluate the highway driving risk. Within the framework, an offline-computed and cached BRS is used online to check whether the car-car interaction safety can be theoretically ensured; if not, a stochastic FRS is then computed online to provide an accurate collision probability.

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