

ITraCS: Interaction-based Trajectory Prediction for Collision Avoidance in Automotive Safety Systems

Abstract

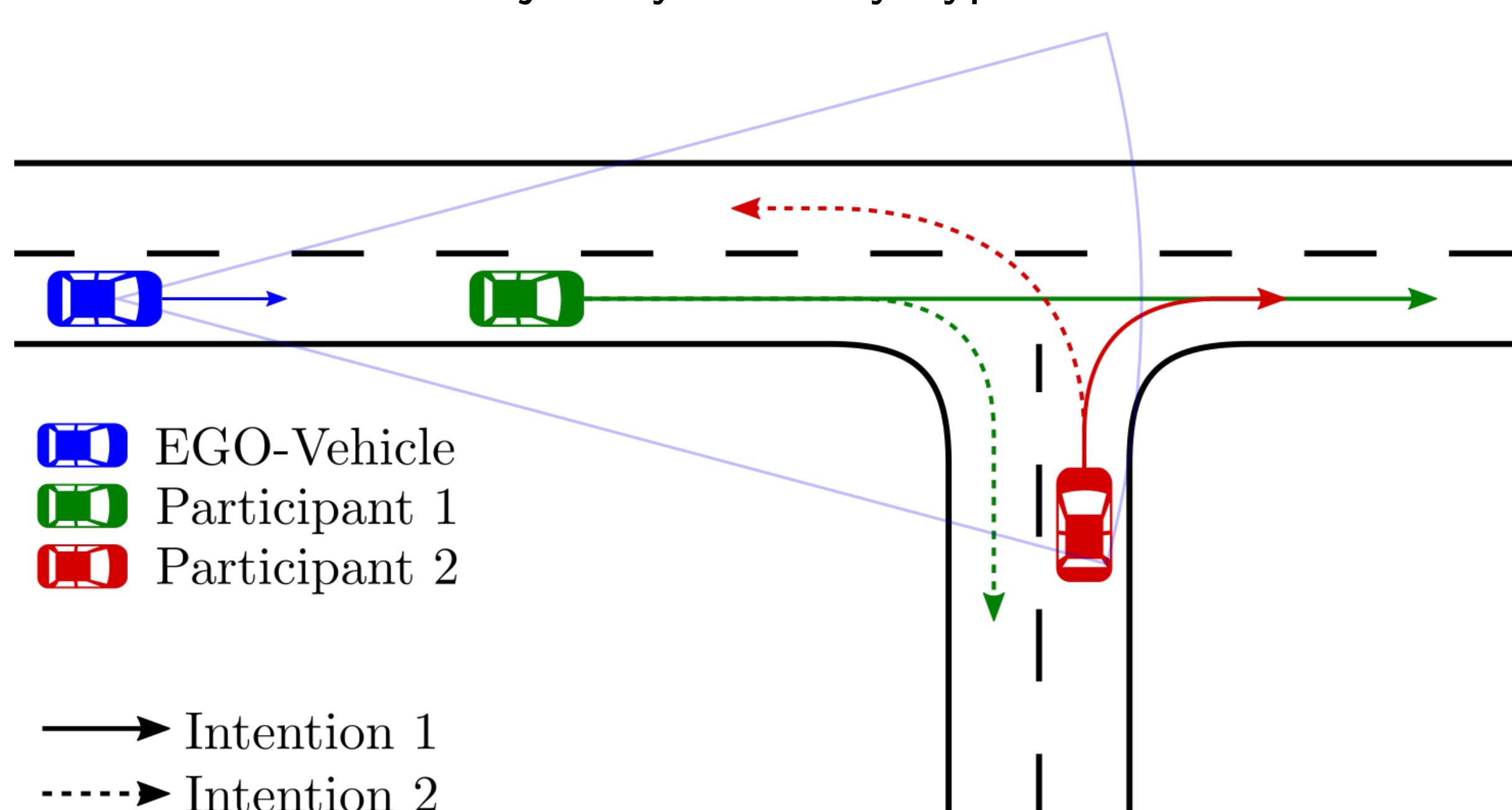
- State-of-the-art active safety systems assume simplified presumptions about environmental events which is unproblematic for short prediction times
- For longer prediction times, the interaction between the traffic participants needs to be properly modeled to accurately predict their movement on longer timescales (typically $> 1\text{ s}$)
- ITraCS aims to model the interaction between traffic participants with a probabilistic model to enable a predictive, deescalative action for a possibly critical situation

Research Question

- How can the interaction of the relevant surrounding traffic participants be modeled with a *probabilistic prediction framework* in a possibly critical situation?
- How can the interaction of traffic participants be efficiently included into a method for the predictive deescalation of critical situations in mixed traffic?

Methodology

- Use of a *Partially Observable Markov Decision Process* (POMDP) [1] to model the state uncertainties of and the interaction between traffic participants
- An *interaction point* defines a traffic scenario, where several traffic participants have to interact with i.e. react to each other in order to avoid a critical situation
- The traffic participants in an *interaction point* are assigned a set of main hypothesis given by infrastructural constraints as part of their state to generate a reference trajectory for every hypothesis



- The EGO-Vehicle acts as an observer approaching the *interaction point* behind another vehicle, therefore an interaction-aware prediction of the situation is needed to safely navigate through the *interaction point*
- Actions are defined to accomodate for trajectories varying from the main hypothesis, e.g. evasive maneuvers due to criticality
- For every action taken, a state-dependant reward is given with respect to the criticality, promoting de-escalative trajectories
- Applying Bellman's principle, every possible action sequence can be evaluated with respect to their long term value

$$V^*(b) = \max_a \left[R(b, a) + \gamma \int_{z \in Z} Pr(z | b, a) \cdot V^*(b') dz \right] \quad (1)$$

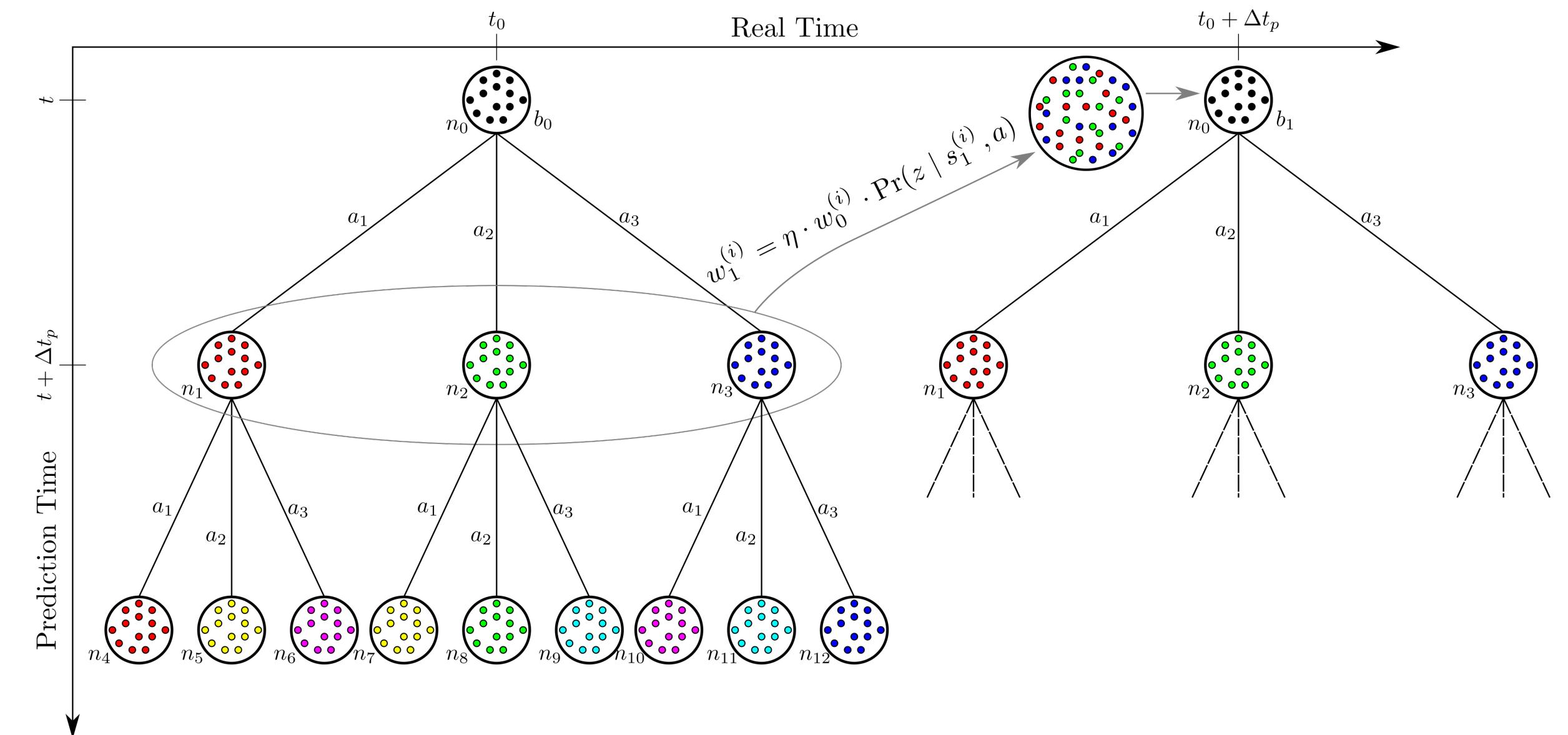
which is intractable for continuous state and/or observation space

- A belief state $b(s)$ is approximated by a weighted ensemble of N particles, so each particle $s_t^{(i)}$ represents a discrete realization of the continuous state space at time t

$$b_t \equiv b(s_t) \approx \sum_{i=1}^N w_t^{(i)} \cdot \delta(s_t - s_t^{(i)}) \quad (2)$$

Methodology

- Applying every possible action to the initially sampled particle ensemble, this results in a belief tree structure



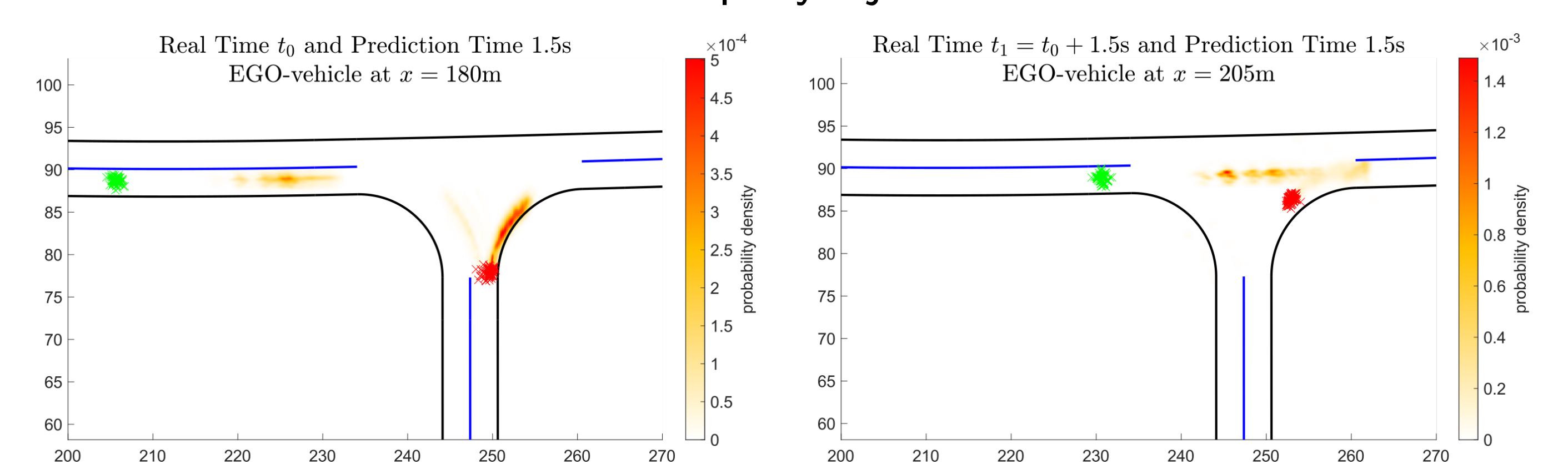
- Using (1), the expected long term reward for a particular belief node in the tree can be estimated, acting as an additional weight ω for the corresponding particles

$$Pr(s | b_0, t_{pred}) \approx \sum_{n \in \mathcal{N}_{t_{pred}}} \omega_n \sum_{i=1}^N w_{t_{pred}}^{(i,n)} \cdot \delta(s - s_{t_{pred}}^{(i,n)}) \quad (3)$$

- At real time $t_0 + \Delta t_p$, a new observation is used to update the particle weights and generate a new observation from all eligible particles at prediction time $t + \Delta t_p$

Proof of Concept

- Simulation results for the exemplary t-junction scenario



Research Focus and Future Steps

- Evaluation and validation of the implemented framework for different scenarios
- Comparison to existing prediction methods
- Utilization of the prediciton output for the EGO-Vehicle decision process in predictive safety functions
- Integration of statistics about real traffic data for generating more realistic reference trajectories to achieve more accurate predictions

References

- [1] M. J. Kochenderfer and C. Amato, *Decision making under uncertainty: Theory and application*. Lincoln Laboratory series, Cambridge, Mass.: MIT Press, 2015.