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# Bipartite Graph Modeling of Critical Driving Scenarios - an Occupant Safety Perspective

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## 1. INTRODUCTION AND MOTIVATION

The automotive industry is currently undergoing major changes. While mobility concepts and drive technologies change, vehicle safety remains of utmost importance and enables new mobility concepts. Currently, the field of vehicle safety systems can be divided into active and passive systems. Within this definition, active systems prevent a crash while passive systems mitigate crash consequences for the occupants. Each system has its intrinsic operating time, activation logic, and principle of action. With the constantly increasing development of enhanced sensor technology for the vehicle's interior and exterior, this can be used for predictive safety strategies Grotz et al. (2021). In addition to improved data availability and increased interconnection between former separated systems, this promises holistically coordinating all safety systems. This approach targets an improved scenario-based occupant protection. To bring vehicle safety from trigger-based activation of individual components and actuators to holistic and comprehensible safety decision-making, a mathematical description of the environment is the crucial first step to begin with the interdisciplinary modeling, simulation and optimization cycle.

In the following, a base scenario is shown and in Section 2 the novel approach of mathematically formulating a driving scenario, from an occupant perspective, as a bipartite graph is presented.

In Fig. 1 the driving scenario is depicted, labelling the vehicle under consideration (ego vehicle) in green. The other road users and potential accident opponents, referred to as bullets hereinafter, in black. Figure 1(a), describes an uncritical driving scene on a two-lane road. Only one passenger, the driver, occupies the the vehicle. If the car ahead decelerates, ideally detectable via the taillights, the ego vehicle needs to react and has different options. If the time-to-collision (TTC) is greater than the time-to-brake (TTB), it is still possible to stop before a collision occurs. However, if the TTC is smaller than the TTB, or if a rear-end collision with a following vehicle ($B_2$) should be avoided, a front collision will occur. Since the left lane is blocked ($B_3$) and there is also an obstacle ($O$) on the right side, an evasive maneuver influences the safety strategy. In the presented scenario, the driver is leaning slightly to the front left, as depicted in Fig. 1(b), i.e. the driver is adjusting something on his mirror.

Emergency braking followed by a collision may not be the ideal safety strategy, as the belt does not well couple the occupant to the vehicle's deceleration, hence the performance of the airbag is reduced. Since the passenger seat is not occupied, a collision on the passenger's right side of the vehicle, as shown in Fig. 1(c), would help to make the impact less critical for the occupant by better exploiting the safety potential of the airbag as the driver is slightly moved towards the center during the impact.

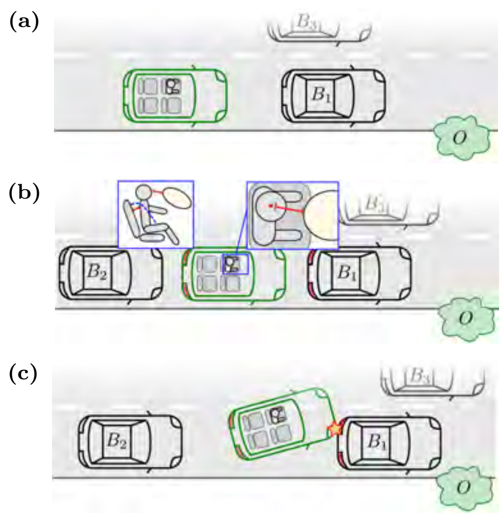


Fig. 1: Driving scenarios (a)-(c) with ego vehicle (green) and bullet vehicles (black).

This presented scenario shows how challenging it is to find the optimized safety strategy which maximizes the benefits of available safety systems for occupant protection. The task becomes even more difficult when considering multiple occupants, the driver's attention status, possible occlusions in the environment, the lack of sensor information, scenario states such as the TTC or the safety parameters of the passive safety devices, e.g. seatbelt pretensioner trigger.

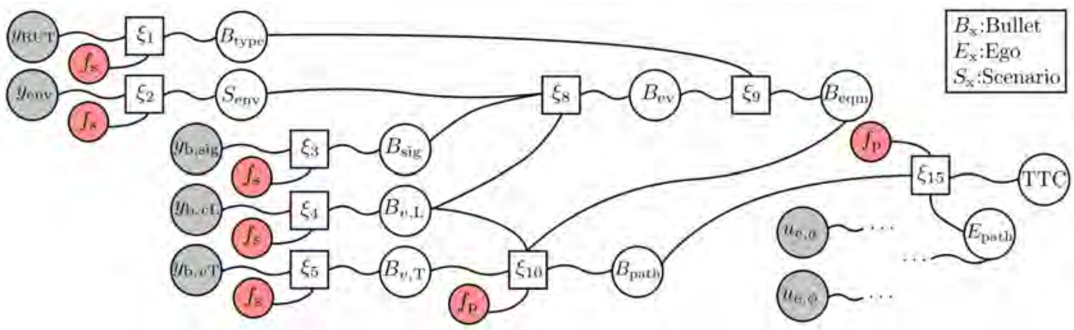


Fig. 2: Branch of a bipartite graph representing a driving scenario with measured inputs (grey) and uncertainties (red).

## 2. MODELING

In order to later decide on a safety strategy for the occupant online, calculations has to be simplified. Thus surrogate models need to be derived for some state relationships. The overall model must be able to combine physical models with data-driven models and expert knowledge and allow for the implementation of uncertainties and probabilities. The following description is limited to a mathematical framework without describing the entire mathematical modeling, which is not the scope of the presented work.

A bipartite graph is used to represent the relationships of the variables and to meet the needs of the model. This approach is presented in Gienger (2021) for process monitoring and fault detection. Figure 2 shows a branch of the overall model. As a bipartite graph, it represents how the TTC can be inferred from sensor data of the environment and the ego vehicle.

The vertices of the graph $\mathcal{G} = (\mathcal{V},\mathcal{U})$ can be split in two groups, where $\mathcal{V}$ represents the variable nodes (circles) and $\mathcal{U}$ represents factor nodes (rectangles), such that every edge conntects between these groups. Variable nodes consist of observable nodes $\{y_{\mathrm{RUT}},\ y_{\mathrm{env}},\ y_{b,\{\mathrm{sig},v\mathrm{L},v\mathrm{T}\}},\ u_{\mathrm{e},\{a,\phi\}}\}$ and latent variables $\{S_{\mathrm{env}}$, TTC, $B_{\{\mathrm{type,sig,ev,eqm,path},v\mathrm{L},v\mathrm{T}\}}$, $E_{\mathrm{path}}\}$ which are unknown and correspond to the states of the system. The red variable nodes describe the sensor uncertainties $f_{\mathrm{s}}$ and the process uncertainties $f_{\mathrm{p}}$ resulting from inaccurate sensing and errors in the mathematical model. The factor nodes $\xi_{1,\dots,15}$ represent the functional dependencies between adjacent variable nodes. This representation of the system dynamics helps to understand the system structure and sets the basis for later implementation. The measured inputs $y_{\mathrm{RUT}} \in \{$car, pedestrian, truck, etc.$\}$ which describe the road user type under observation, and $y_{\mathrm{env}} \in \{$crossing, left/right lane, turn, etc.$\}$ describe the current environment give information about which maneuvers the observed bullet may potentially execute. The derived states $B_{\mathrm{type}}$ and $S_{\mathrm{env}}$ contain the probabilities of the measured inputs. Combined with some evidence $y_{\mathrm{b,sig}} \in \{[0,1];[0,1]\}$ representing the status of the turning signals of the bullet, $y_{\mathrm{b},v\mathrm{L}}$ and $y_{\mathrm{b},v\mathrm{T}}$ representing the measured lateral and tangential velocity of the bullet and their states including the uncertainties $B_{\{\mathrm{sig},v\mathrm{L},v\mathrm{T}\}}$, an equation of motion $B_{\mathrm{eqm}}$ for the most likely maneuver is selected. The evaluation of the selected equation $B_{\mathrm{eqm}}$ with the measured velocities results in a predicted path $B_{\mathrm{path}}$. This procedure is similar to the approach presented by Schreier et al. (2016). For the ego vehicle and its input states $u_{\mathrm{e},a}$, describing the acceleration, and $u_{\mathrm{e},\phi}$, describing the steering angle, a graph is defined leading to a predicted ego path $E_{\mathrm{path}}$. This branch is omitted in Fig. 2 for better readability. Given the two paths, the TTC is calculated with a process uncertainty $f_{\mathrm{p}}$. So in this branch of the bipartite graph a TTC is derived from both a probabilistic model to assume a maneuver of the bullet and a physical model in forms of the equation of motion.

## 3. CONCLUSION AND OUTLOOK

The interconnection between active and passive safety systems in different driving scenarios can offer enormous benefits for the occupant's safety. A mathematical description of the traffic environment is mandatory to decide model-based when and which system should intervene. In this work, an approach was presented how a complex traffic scenario can be described mathematically and how the relationships of different variables can be represented. The representation as a bipartite graph can combine different modeling approaches, including probabilities and uncertainties and attaching a decision tree as in Bungartz et al. (2013) Ch. 3-4. This leads to the goal of finding a holistic safety strategy that helps to optimally utilize the safety potentials of the individual components. In further investigations, the branches of the graph will be extended and different modeling approaches will be used and tested in a simulation environment. For state dependencies that either cannot be physically described or can only be calculated with great computational effort naturalistic driving- and crash databases like, e.g. the AMP or GIDAS will be used.

## REFERENCES

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