Master's Thesis

Collision avoidance by autonomous braking and steering

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Abstract

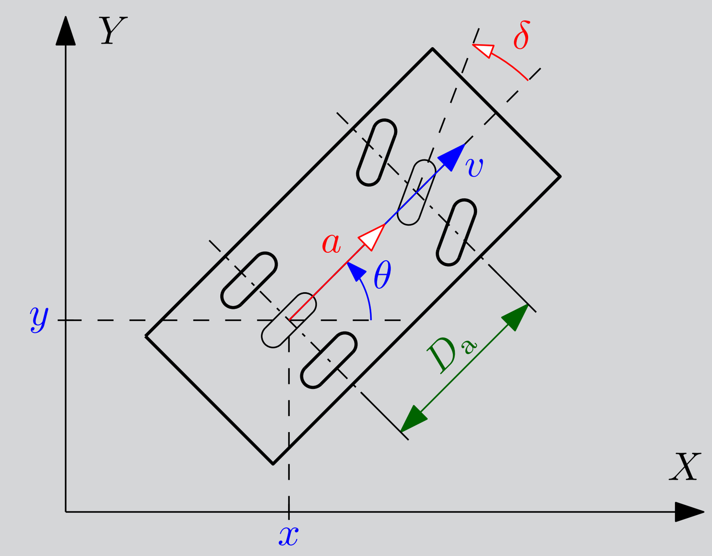
Driver assistance systems have become more and more important in recent years due to the increasing degree of automation in road traffic – especially with regard to increasing safety. These systems do not only provide passive protection for driver and passengers (e.g. through airbags), but – in the near future – will also be able to protect other road users from injury by actively avoiding collisions. Emergency brake assistants are already mandatory for newly registered trucks and buses, and these assistants are becoming increasingly important also in civil road traffic. The next stage of development will be assistance systems that can carry out not only emergency braking independently but – if necessary – also steering manoeuvres if those are required to avoid a collision.

This thesis deals with such an autonomous braking and steering assistant that intervenes in critical situations to avoid accidents. The aim of this thesis is to develop a system that can follow a given route under normal conditions and takes action if necessary, namely if obstacles or other road users would involve the vehicle in an accident. For this purpose, a simple model of a real vehicle is created, including model boundaries and physical limitations. Subsequently, a mathematical formulation of the environment as well as of various other road users is developed – the group of possible dynamic objects is limited to passenger cars, cyclists, and pedestrians. In the next step, an optimisation problem is formulated with the aim to avoid collisions and to follow the original path as well as possible. In each optimisation step, this is done in a two-layer structure. In the first layer, non-linear model predictive control (NMPC) with a prediction- and control-horizon of $5\,\mathrm{s}$ is used to check which of the available lanes has the lowest risk for a collision. This lane is then selected as the reference for the next layer if the risk of a collision on the primary lane exceeds a certain limit in this step. In the second layer, the selected trajectory is tracked as well as possible by an NMPC – taking into account the existing collision risk – with the additional involvement of other road users. This happens with a now shorter prediction- and control-horizon of $2\,\mathrm{s}$. In order to be able to estimate the behaviour of other road users, a prediction model is introduced which deduces from the states of the objects to their inputs and predicts their future behaviour. In order to evaluate this model, data from real road users were recorded by using a test-vehicle, and were analysed later on. In a final step, the developed collision avoidance assistant is applied to a selected set of scenarios. The resulting trajectories are then validated using a realistic vehicle model in IPG CarMaker to obtain information about the modelling quality.

Modelling of the ego-vehicle

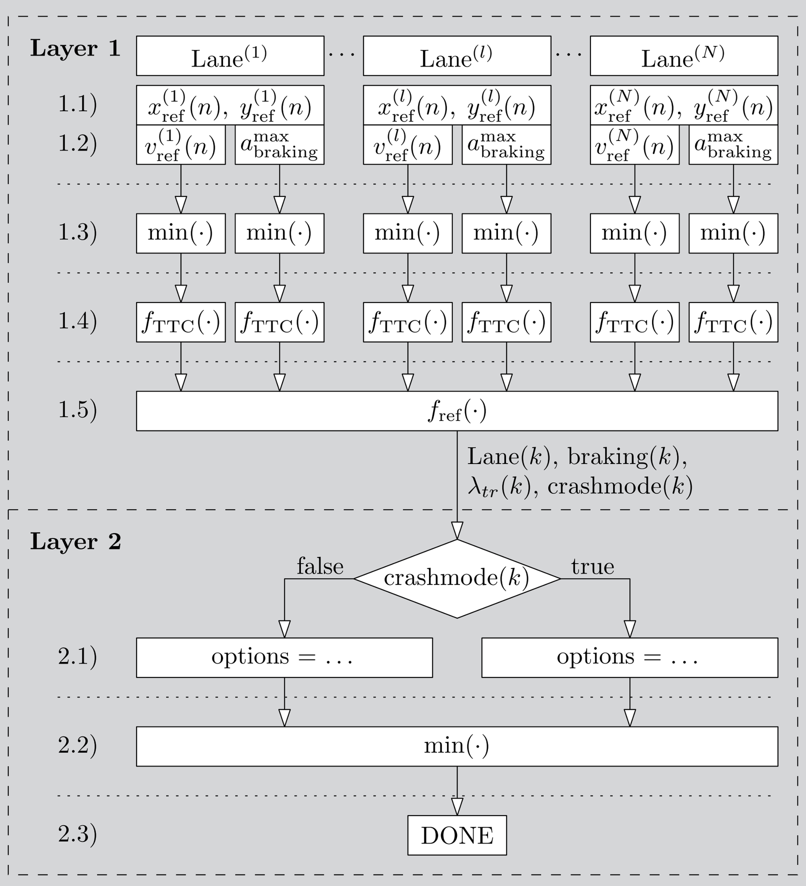
For the ego-vehicle, a single-track model is selected. It contains four states (position $x(t)$ and $y(t)$, velocity $v(t)$ and orientation $\theta(t)$) as well as two inputs (acceleration/deceleration $a(t)$ and steering angle $\delta(t)$). D_a expresses the axle spacing of the vehicle.

$$\frac{\mathrm{d}}{\mathrm{d}t}x(t) = v(t)\cdot\cos(\theta(t))$$
$$\frac{\mathrm{d}}{\mathrm{d}t}y(t) = v(t)\cdot\sin(\theta(t))$$
$$\frac{\mathrm{d}}{\mathrm{d}t}v(t) = a(t)$$
$$\frac{\mathrm{d}}{\mathrm{d}t}\theta(t) = \frac{v(t)}{D_a}\cdot\tan(\delta(t))$$



By using the simple forward Euler method, the proposed continuous-in-time model is transformed to a discrete-in-time model with $T_\mathrm{s} = 0.1\,\mathrm{s}$ as the sample time of the system. The presented model is used for all further applications in this work, which means that no mismatch between the NMPC-model and the process is assumed. This assumption is later validated offline using a high-degree-of-freedom model by tracking the generated trajectories with IPG Carmaker.

Optimisation



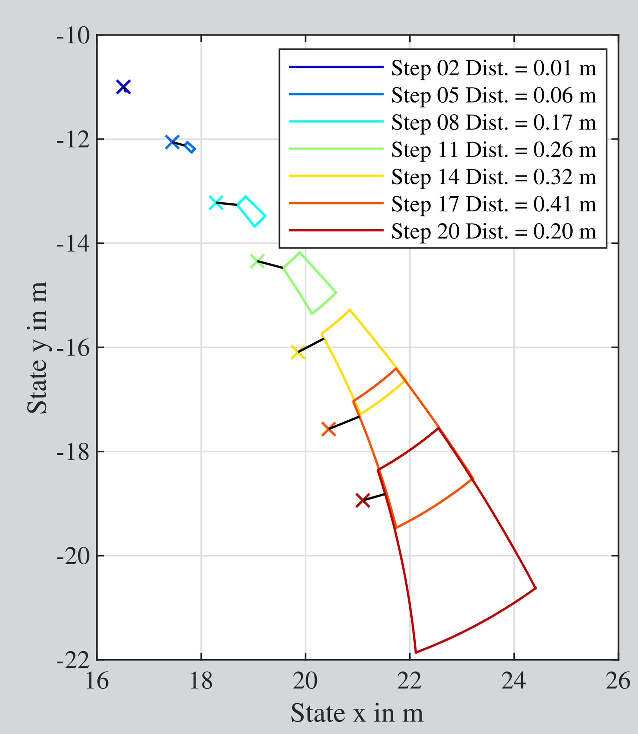
A two-layer approach is used to provide optimal results. In the first layer, a set of possible trajectories – using all available lanes – is generated. Then, the safest one of these trajectories is selected – with some heuristics in the background to keep the focus on the primary planned lane – except when it gets too dangerous.

Time to collision (TTC) to the predicted positions of surrounding obstacles acts as a performance criterion for the specific trajectories.

The second layer then tries to track the selected trajectory, but additionally minimizes the risk of a collision by avoiding obstacles along the trajectory through braking and steering. This procedure happens in each optimisation step, the concept is shown in the picture.

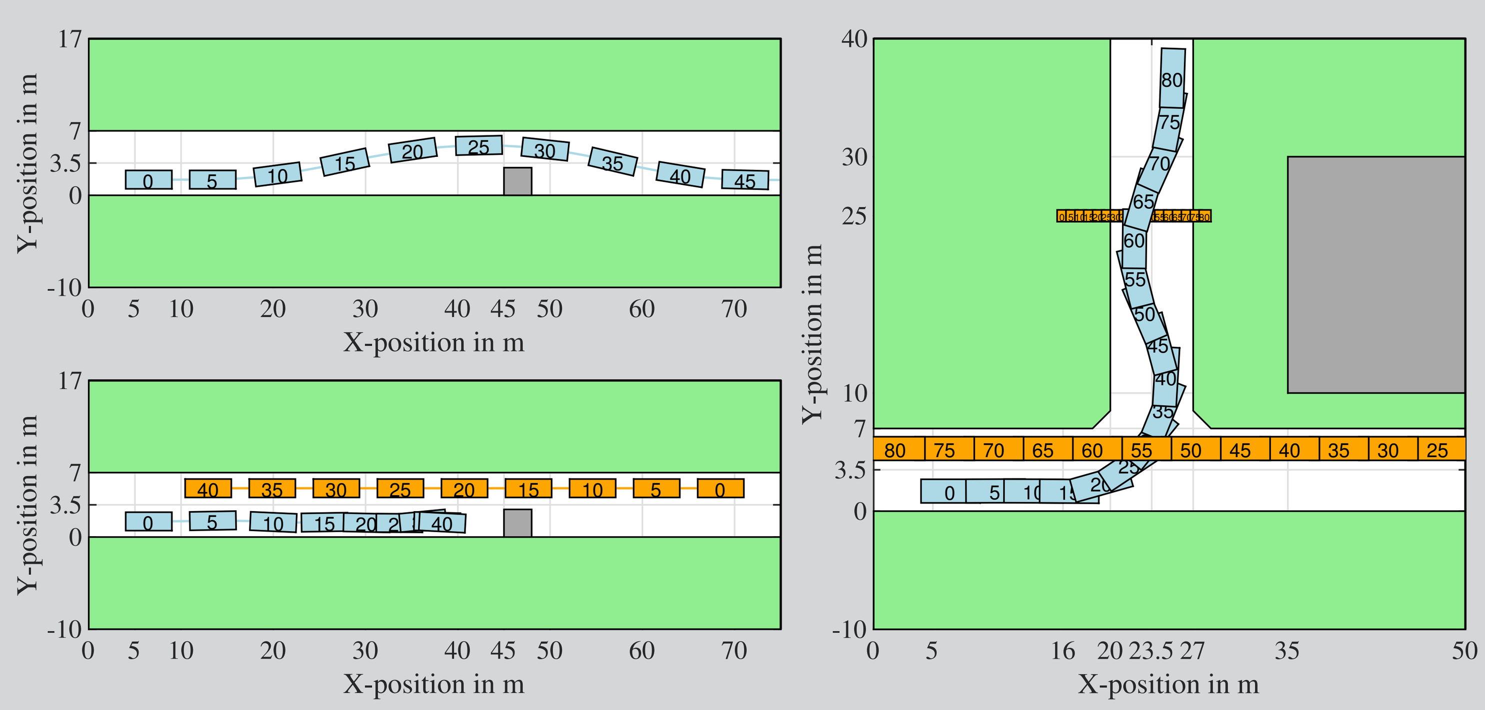
Prediction

In this work, a single trajectory simulation is combined with the amount of dynamics defined by the previous movement of the obstacle to get a field of future object states that evolves and gets bigger with each prediction step. Previous dynamics in movement are taken into account to trim future states to a reduced set. The single-track model is used for the prediction. In general, the states of such a system vary over time, which can easily be observed when looking at cars in the real world, while inputs of the system (in this case acceleration or deceleration $a(k)$ and steering angle $\delta(k)$) remain mostly equal during static manoeuvres and only vary when a different manoeuvre is chosen or to readjust the movement during an ongoing manoeuvre. Based on this hypothesis, the prediction algorithm relies on the estimated inputs of the system and not on the states. Therefore, a method to calculate inputs based on available states is required, assuming that all states of the vehicle are measured. For $k = k^* - M_\mathrm{s}, \ldots, k^*$ measured states, the estimation of the inputs can be performed by simply reshaping and solving the equations for $a^{\mathrm{est}}(k)$ and $\delta^{\mathrm{est}}(k)$. $v^{\mathrm{s}}(\cdot)$ as well as $\theta^{\mathrm{s}}(\cdot)$ represent the entries of the measured state vectors smoothed with the function csaps in MATLAB® to cancel the influence of potential measurement noise on the prediction. The prediction error is defined as the distance between actual measured position-states and the predicted field where the position is assumed to be. As the LIDAR system, which was used to obtain measurement data, was only capable of measuring the outer dimensions of obstacles, it was not possible to determine the distance D_a between the obstacle axles. Therefore, the median of common values was used for the specific types. As pedestrians have no actual axle spacing, the value was selected significantly smaller compared to cars and bicycles to model their capability of fast direction changes. The selected values are $D_\mathrm{a}^{\mathrm{car}} = 2.5\,\mathrm{m}$, $D_\mathrm{a}^{\mathrm{bicycle}} = 1.1\,\mathrm{m}$ and $D_\mathrm{a}^{\mathrm{pedestrian}} = 0.5\,\mathrm{m}$.



Scenarios and Results

The assistant was tested using scenarios, three of them are shown in this section. All results were also validated by tracking the resulting trajectories with a high-degree-of-freedom model implemented in IPG Carmaker. All scenarios could be tracked without significant deviation. Therefore the used single-track model is confirmed as sufficient. As expected, the assistant avoids collisions with the obstacles by braking and steering. Depending on the behaviour of other road users, the assistant adapts the trajectory of the ego-vehicle (light blue).



Conclusions and Outlook

The developed system is able to avoid collisions in all observed scenarios, and the general behaviour seems promising, because the system reacts as expected. More measurements of general and also critical traffic situations will follow, as well as a catalogue of critical testing scenarios – or even other methods for the safety evaluation of such a system – to contribute to a further development of the system. An implementation of this method for extra-urban applications would be interesting, as the current system was developed and tested only for urban scenarios with up to $50\,\mathrm{km/h}$. To sum up, there is to say that the two-layer approach leads to promising results that should be further investigated.