

# Situation analysis and decision making for active pedestrian protection using Bayesian networks

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**Abstract**—One of the major challenges in advanced driver assistance systems is the interpretation of available environment information. It is the foundation for system activation strategies and decision making. Often deterministic motion models are used to predict pedestrian movements, which leads to constricted validity. Investigations have shown that uncertainty is not negligible in pedestrian models due to their high dynamic range. Standard concepts of decision making are not able to deal with uncertain motion models. Decision making gets even more difficult if different emergency maneuvers can be selected, i.e. emergency braking, evasive steering or a combination of both. The benefit of each of these maneuvers depends highly on the future position of the pedestrian. An appropriate maneuver can hardly be selected based on a deterministic pedestrian model. Here, a probabilistic approach to situation analysis based on a pedestrian model with uncertainty is suggested. An emergency maneuver is selected considering the optimal injury risk reduction for the pedestrian.

## I. INTRODUCTION

Advanced driver assistance systems are available in an increasing amount of new vehicles. These systems are able to increase driving comfort as well as safety [1], due to recent surround view sensor systems and methods for situation analysis. Typically such systems are designed in a hierarchical structure, where a sensor provides information of the vehicle environment. This data is further used to generate an environmental model and extract situational knowledge, as stated in [2], [3]. In particular, predicting future behaviour of the driver and other road users is a challenging task for driver assistance systems. For example, in [4] a collision avoidance system using sensor data fusion of radar, video and laser sensors is shown to increase the quality of the environment model. Other systems focus on handling uncertain information for more realistic situation interpretation [5], [6], [7].

The presented paper focuses on a driver assistance system for pedestrian protection. Therefore it is focused on motion modelling and prediction for vehicles and pedestrians in collision scenarios. The special challenge of pedestrian motion prediction is a high dynamic range of possible movements. This leads to a highly uncertain predictability. The uncertainty can be reduced by restricting pedestrian dynamic to physiological possible limits [8] or corresponding to experimental investigations as stated in [9]. Other systems further consider uncertainty in pedestrian motion prediction, as stated in [10].

In [11] a method for determining the time-to-collision (TTC) under uncertainty is introduced.

In the following, a method for a probabilistic situation analysis will be presented. A hybrid Bayesian network will be introduced for motion prediction of critical driving scenarios with pedestrians. Uncertainties of pedestrian behavior models and measurements will be considered. The pedestrian motion prediction is based on the experimental research of [12]. Besides assessing a collision risk, the effect of possible emergency maneuvers is evaluated. Since drivers are able to influence emergency maneuvers, in particular evasive maneuvers with steering wheel intervention, the results of an according end-user study [13] are considered. The output of the Bayesian network is a mixture of multivariate Gaussian distributions to describe the scenario as well as the effect of different emergency maneuvers. To identify the driving maneuver with the lowest injury risk probability for the pedestrian a maneuver decision as stated in [14] is used.

## II. SYSTEM DESIGN

A major task of an active pedestrian protection system is the situation interpretation and resulting system activation. Therefore it is necessary to predict the future motion of the vehicle and the pedestrian. In the following, scenarios with one vehicle and one pedestrian are considered. The initial state  $s_{\text{veh}}(t_0)$  of the vehicle is basically measured by inertial sensors and represented by its normally distributed velocity  $v_{\text{veh}} \sim \mathcal{N}(\mu_{v,\text{veh}}, \Sigma_{v,\text{veh}})$  defined in driving direction, as well as the corresponding steering angle  $\delta_{\text{veh}} \sim \mathcal{N}(\mu_{\delta,\text{veh}}, \Sigma_{\delta,\text{veh}})$  and orientation  $\psi_{\text{veh}} \sim \mathcal{N}(\mu_{\psi,\text{veh}}, \Sigma_{\psi,\text{veh}})$ . The vehicle state  $s_{\text{veh}}(t)$  is defined as:

$$s_{\text{veh}}(t) = [x_{\text{veh}}(t), y_{\text{veh}}(t), v_{x,\text{veh}}(t), v_{y,\text{veh}}(t), \delta_{\text{veh}}(t), \psi_{\text{veh}}(t)]^T \quad (1)$$

The pedestrian's state  $s_{\text{ped}}(t)$  is equivalent to equation (3) and contains for  $t=t_0$  values measured by a surround view sensor. Additionally a multivariate density distribution of pedestrian positions in  $x$ - and  $y$ -direction  $d_{\text{ped}}$ , as well as the corresponding distribution of vehicle positions  $d_{\text{veh}}$  are defined. The origin of the underlying coordinate system is

defined at the center of the vehicle front for  $t=t_0$ .

$$d_{\text{ped}} \sim \mathcal{N}(\mu_{d,\text{ped}}, \Sigma_{d,\text{ped}}) \quad (2)$$

with  $\mu_{d,\text{ped}} = (\mu_x, \mu_y)^T$

$$s_{\text{ped}}(t) = [x_{\text{ped}}(t), y_{\text{ped}}(t), v_{x,\text{ped}}(t), v_{y,\text{ped}}(t), \psi_{\text{ped}}(t)]^T \quad (3)$$

To perform a motion prediction based on the above mentioned states  $s_{\text{ped}}(t_0)$  and  $s_{\text{veh}}(t_0)$ , prediction models for pedestrian and vehicle are required. Section II-A describes appropriate prediction models. Further section II-B introduces a method to model relations and dependencies by using a hybrid Bayesian network. The output of the Bayesian network represents the distribution of the pedestrian position and velocity relative to the vehicle within a defined prediction time. This distribution is used in section II-D to obtain the corresponding collision risk within  $\tau$  using the contour models for the pedestrian and vehicle as introduced in section II-C. Decision making and maneuver selection will finally be shown in section II-E.

#### A. Motion prediction

Since pedestrians are able to perform high dynamic movements, adequate models are required to restrict the possible dynamic into realistic assumptions. In the following the motion model stated in [12] will be used. It is based on an experimental study to identify maximum acceleration and deceleration potential relating to an initial velocity and motion direction. Besides the pedestrians dynamic range, a probability distribution within this dynamic range is required. As an initial assumption the distribution will be defined as uniformly distributed. To simplify the following calculation steps, it will be approximated by a weighted mixture of Gaussian distributions. This approach further allows to consider other probability distributions, like motion transitions as stated in [15] or motion prediction based on movement detection from specific body parts as introduced in [7].

Motion prediction for the vehicle is divided in different possible maneuvers  $j$ . As a reference maneuver  $j=0$  the actual vehicle motion is predicted using a CA model, which assumes a constant acceleration and a constant steering angle within the prediction horizon. In addition, different emergency maneuvers are defined. This paper will concentrate on a emergency braking maneuver  $j=1$ , as well as a combined braking and steering maneuver  $j=2$ . The emergency braking maneuver is modeled using realistic braking performance of a prototype vehicle with ESC as a hydraulic actuator. The combined braking and steering maneuver considered here uses an electric power steering for lateral system intervention. Since the driver is able to overrule or amplify such a steering intervention, this effect has to be considered in the corresponding motion model. The results of the end-user study, as published in [13], are used to quantify the drivers' influence and adapt the motion model using appropriate assumptions. The longitudinal braking performance of the combined maneuver is slightly reduced compared to an emergency brake.

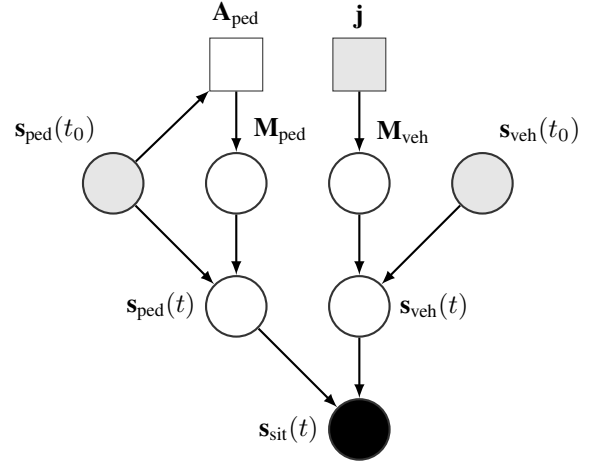


Figure 1. Bayesian network for motion prediction

#### B. Bayesian network

The representation of relations between measurement data and model assumptions is realized using a Bayesian network as shown in figure 1. It allows to visualize dependencies in a comprehensible structure. Nodes of the Bayesian network represent random variables with positions, velocities and corresponding prediction variables. The nodes are structured in a directed acyclic graph, where edges represent conditioned dependencies. Measured data will be used as evidence (light gray) for the top layer nodes, which are drawn as circles for continuous data and rectangles for discrete probability variables. The output (black) of the Bayesian network is a mixture of multivariate Gaussian distributions containing the relative position and velocity of the pedestrian regarding the vehicle for a specific prediction time  $\tau$ .

In [16] and [17] methods for belief propagation in continuous and hybrid Bayesian networks are introduced. Regarding to the fixed structure and evidence only influencing nodes without parents of the proposed network, the inference can be computed top down.

The left part of the network in figure 1 describes the motion prediction for the pedestrian. The node  $s_{\text{ped}}(t_0)$  represents the measured state of the pedestrian. Regarding to the used motion model of [12], the initial pedestrian velocity is classified into its most probable state:

$$A_{\text{ped}} \in \{\text{Standing, Walking, Jogging, Running}\} \quad (4)$$

The continuous node  $M_{\text{ped}}$  represents the future dynamic of the pedestrian and is conditioned by the state of  $A_{\text{ped}}$ . Since [12] defines a range of possible accelerations for each initial state, this range is represented as an approximating mixture of Gaussian distributions. The linear dependency of the predicted state  $s_{\text{ped}}(t)$  is given by physical relations of the initial state  $s_{\text{ped}}(t_0)$  and the used motion model  $M_{\text{ped}}$ .

In a similar way the future motion of the vehicle is predicted assuming a specific driving maneuver and its corresponding motion model  $M_{\text{veh}}$  including longitudinal and lateral dynamics. The predicted, continuous state of the vehicle is  $s_{\text{veh}}(t)$ .

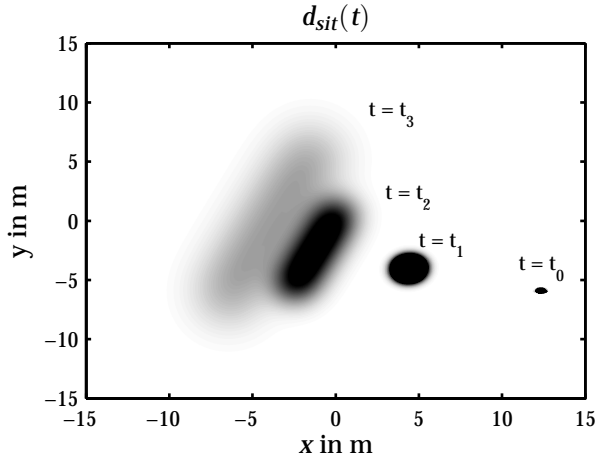


Figure 2. Output for different prediction times

Finally the results of the motion models are combined in a state representing the predicted situation  $s_{\text{sit}}(t)$ . In particular, the position  $d_{\text{sit}}$  is defined by

$$d_{\text{sit}}(t) = d_{\text{ped}}(t) - d_{\text{veh}}(t) \sim \mathcal{N}(\mu_{\text{sit}}(t), \Sigma_{\text{sit}}(t)) \quad (5)$$

Figure 2 shows the output node for different prediction times of the same initial state, containing mixtures of multivariate density functions for the relative position  $d_{\text{sit}}(t)$ .

Due to its modular structure, the introduced method allows to include further knowledge of pedestrian motion or driver interaction. The discrete nodes  $\mathbf{A}_{\text{ped}}$  and  $\mathbf{j}$  are expandable to a partial network of discrete nodes modelling more detailed dependencies. The partial networks can be solved as stated in [18] thereby  $\mathbf{A}_{\text{ped}}$  and  $\mathbf{j}$  will be used as interface nodes to the continuous part of the Bayesian network.

### C. Geometric modeling

In order to estimate the collision risk it is necessary to define a formal condition for a collision. For this reason geometric models for the pedestrian and the vehicle are introduced. The function  $g_{\text{veh}}(x, y, s_{\text{veh}}(t))$  describes the geometry of the vehicle and is 1, if a point with coordinates  $x$  and  $y$  is inside the vehicle contour at time  $t$  and 0 otherwise. In figure 3 the vehicle model  $g_{\text{veh}}$  is displayed in gray for time  $t_0$ . Accordingly,  $g_{\text{ped}}(x, y, s_{\text{ped}}(t))$  is 1 if  $x, y$  is inside the contour of the pedestrian at time  $t$  (see figure 3). The functions  $g_{\text{veh}}$  and  $g_{\text{ped}}$  consider the actual shape of the vehicle and pedestrian for  $t = t_0$ . For  $t \neq t_0$ , a shift in the position, as well as a rotation according to the predicted states  $s_{\text{veh}}(t)$  and  $s_{\text{ped}}(t)$  are considered.

The collision risk estimation, as introduced in section II-D, is based on the relative distance  $d_{\text{sit}}$ , achieved by the motion prediction from section II-B. For this reason a combined geometric model  $g_{\text{sit}}(s_{\text{veh}}(t), s_{\text{ped}}(t))$  is defined as 1, if the corresponding pedestrian model has any intersection with the vehicle model. the combined model is displayed in figure 4.

The resulting time-variant geometric model  $g_{\text{sit}}(t)$  therefore represents the combined contour of the vehicle and pedestrian for each prediction time.

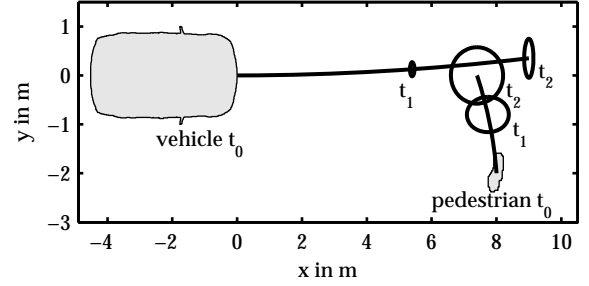


Figure 3. Exemplary situation

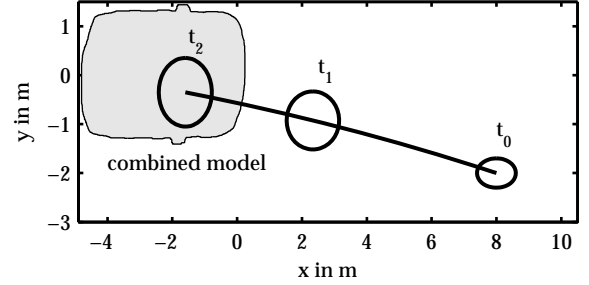


Figure 4. Combined situation

### D. Collision risk estimation

To detect an imminent collision of the vehicle with a pedestrian within the specified prediction period  $T = \{t | t \in [t_0, t_0 + \tau]\}$ , it is necessary to estimate the collision risk  $p_{\text{coll}}$  within this period. In this section a method for collision risk estimation is introduced. The method is based on the predicted position  $d_{\text{sit}}(t)$  for all  $t \in T$  as described in section II-B. Further the geometric models, in particular the combined geometric model  $g_{\text{sit}}$  from section II-C are used.

Figure 3 shows one situation as an example. The vehicle is assumed to drive straight ahead. A pedestrian crosses the vehicle's driving corridor from the right side. The predicted trajectories of the vehicle and pedestrian are shown. In particular, the solid lines in figure 3 show the means of the predicted trajectories. Exemplarily, the standard deviations of the predictions are indicated by ellipses for two timestamps  $t_1$  and  $t_2$ . Figure 4 shows the situation with the combined models assuming  $\psi_{\text{veh}}(t) = \psi_{\text{ped}}(t) = 0$  for all  $t \in T$ .

It can be seen, that the geometric model of the vehicle is extended by the pedestrian geometric model. The combined state  $s_{\text{sit}}(t)$  can be interpreted as the motion observed in the driving vehicle. In general, the probability of the pedestrian position being inside certain limits can be obtained by solving the integral over the density function  $d_{\text{sit}}(t)$  for a specific time  $t$ .

$$P(x_1 \leq x \leq x_2, y_1 \leq y \leq y_2) = \int_{x_1}^{x_2} \int_{y_1}^{y_2} \frac{1}{2\pi |\Sigma_{\text{sit}}(t)|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2} \Theta^T \Sigma_{\text{sit}}(t)^{-1} \Theta\right\} dx dy \quad (6)$$

with

$$\Theta = ([x, y]^T - d_{\text{sit}}(t)) \quad (7)$$

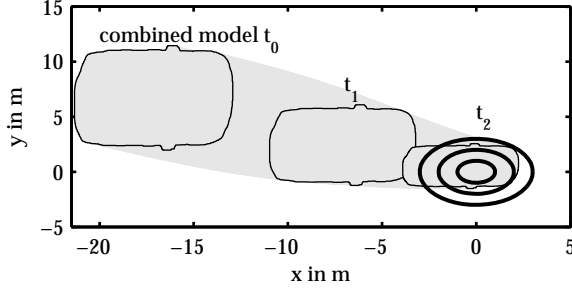


Figure 5. Normalized situation

For criticality assessment the collision risk  $p_{\text{coll}}$  is calculated by solution of this integral for all  $t \in T$  and using the corresponding geometric model  $g_{\text{sit}}(t)$  as integration limits. Since  $d_{\text{sit}}(t)$  and  $g_{\text{sit}}(t)$  depend on a specific prediction time, the integration over different density functions with different integration limits would be necessary and lead to a challenge in calculating the resulting collision probability. However, a practical approach is to normalize  $d_{\text{sit}}(t)$  to a standard normal distribution where the symmetric covariance matrix  $\Sigma_{\text{sit}}$  is decomposed by a singular value decomposition as follows:

$$\Sigma_{\text{sit}} = U \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} U^T \quad (8)$$

To normalize the density function  $d_{\text{sit}}(t)$  is substituted by  $z$ :

$$z = U \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix} U^T (d_{\text{sit}} - \mu_{\text{sit}}) \quad (9)$$

To calculate  $p_{\text{coll}}$  the integral is computed over the area  $A$ .  $A$  is defined as the area enveloped by  $g_{\text{sit}}(t)$  for all  $t \in T$ , as marked in gray in figure 5. Finally the collision probability  $p_{\text{coll}}$  can be calculated as

$$p_{\text{coll}} = \iint_A f_z(z) d^2z \quad (10)$$

with

$$f_z(z) = \frac{1}{2\pi} \exp\left\{-\frac{1}{2}z^T z\right\} \quad (11)$$

In figure 5, the standard normal distribution of  $d_{\text{sit}}(t)$ , as well as an analogously transformed geometric model  $g_{\text{sit}}(t)$  for time stamps  $t_0, t_1$  and  $t_2$  are illustrated. For example, the collision risk for prediction time  $t=t_3$  of figure 2, is  $p_{\text{coll}}=0.8$ . The validation of this method was done performing Monte Carlo experiments for the same motion prediction. The collision risk can then be obtained by calculating the percentage of trajectories crossing the geometric model.

1) *Example:* The following example shows a simplification of the above described method, assuming only collisions with the vehicle front and without rotation of the geometric model  $\psi_{\text{veh}}(t) = 0$  for all  $t \in T$ . The geometric model for the vehicle is therefore only defined by a line in  $y$ -direction from  $-\frac{w_{\text{veh}}}{2}$  to  $\frac{w_{\text{veh}}}{2}$ , with  $w_{\text{veh}}$  as the length of the vehicle's front. The pedestrian's geometric model will be reduced to a point at

its own origin. Assuming that  $z$  from equation (9) is strictly monotonic increasing in  $x$ -dimension the collision risk  $p_{\text{coll}}$  can be determined by solving the integral

$$p_{\text{coll}} = \iint_A f_z(z) d^2z \quad (12)$$

$$= \int_{\chi(t_0)}^{\chi(t_0+\tau)} \int_{\phi(\chi^{-1}(x)-\frac{w_{\text{veh}}}{2})}^{\phi(\chi^{-1}(x)+\frac{w_{\text{veh}}}{2})} f_z(z) d^2z \quad (13)$$

whereby the functions  $\chi(t)$  and  $\phi(t)$  are defined as

$$\begin{bmatrix} \chi(t) & \phi(t) \end{bmatrix}^T = z(t) \quad (14)$$

and  $\chi^{-1}$  is the inverse function of the invertible function  $\chi$ . Further it is possible to write  $p_{\text{coll}}$  dependent from  $t, \phi(t), \chi(t)$  and its derivative  $\chi'(t)$ :

$$p_{\text{coll}} = \int_{t_0}^{t_0+\tau} \int_{\phi(t)-\frac{w_{\text{veh}}}{2}}^{\phi(t)+\frac{w_{\text{veh}}}{2}} f_d(\chi(t), y) \chi'(t) dy dt \quad (15)$$

with

$$f_d(x, y) = f_z(z) \quad (16)$$

Then an analytical solution for the collision probability can be calculated from equation (12).

### E. Maneuver decision

The final task of the introduced pedestrian protection system contains decision making. If a sufficiently high collision risk (see section II-D) is estimated, each of the prediction maneuvers  $j$  (see section II-A) will be rated regarding their effect. In particular, the reduction of the pedestrian's injury risk is used to determine the benefit  $\xi$  of each emergency maneuver regarding the reference maneuver as introduced in [14]. If there is an emergency maneuver  $j_{\text{opt}}$  resulting in an injury risk lower than all other maneuvers, especially the reference maneuver  $j=0$ ,  $j_{\text{opt}}$  will be executed by the system.

## III. SYSTEM VALIDATION

An end-user study with 23 test person was carried out for system validation. The test person were instructed to drive on a track with parking vehicles on the ride side. During one test run with 50kph a pedestrian dummy appears surprisingly for the test person and enters the drive lane, as shown in figure 6. The timing is chosen, that a normal driver is not able to avoid the collision by an emergency braking maneuver, however steering can lead to collision avoidance. Overall 35 valid test runs are recorded for system validation. In 8 of these tests the driver was able to initiate an emergency maneuver, before the system detected a sufficiently high collision risk. This leads to an amount of 27 evaluable data sets. In 20 test runs (set-up 1) the pedestrian dummy was entering the road 0.5m, in 7 further tests (set-up 2) the dummy was moved 1m inside the driving lane. The video data and additional driver inputs like steering and pedal interactions are used to perform a subsequent simulation. In set-up 1 the expected system behaviour is a high collision risk estimation and a maneuver decision favoring an combined braking an steering



Figure 6. Video data of end-user study

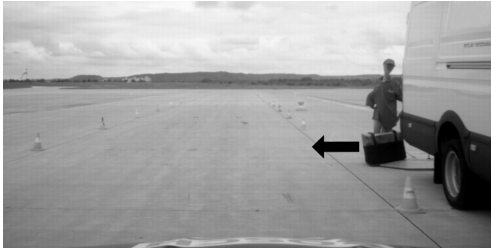


Figure 7. Example for system activation

maneuver. In set-up 2 the collision risk and maneuver decision should lead to an emergency braking maneuver.

The results of set-up 1 show, that in 13 of 20 test runs the proposed system directly selected the combined braking and steering maneuver. In 7 data sets, an emergency braking maneuver was chosen due to the predicted collision.

In test set-up 2 an emergency braking maneuver was triggered in 4 of 7 data sets. For 3 situations a combined braking and steering maneuver was selected, two of them regarding to a steering interaction started by the driver shortly before the actual system activation.

Finally, figure 7 shows an example situation at the time of system activation. The pedestrian is detected besides the drive lane by the surround view sensor. Due to the vehicle speed of  $12.87 \frac{m}{s}$  and a measured pedestrian lateral velocity of  $1.58 \frac{m}{s}$  the motion models predict a high collision risk and an emergency maneuver for collision avoidance is triggered.

#### IV. CONCLUSIONS

The paper introduced a method to combine the motion prediction of pedestrians and vehicles. The approach allows different types of motion models for vehicles and pedestrians, even for complex driving maneuvers. In particular, emergency maneuvers like emergency braking or evasive maneuvers including the driver influence are modeled. The motion prediction produces a multivariate mixture of Gaussian distributions describing the relative position of the pedestrian relating to the vehicle. Further, the collision risk within a defined prediction time is obtained based on the prediction output. The system design is implemented to perform subsequent simulations of recorded video data and vehicle data including driver interactions. A first validation is done by using data of an end-user study with naïve drivers. The validation shows comprehensible results, even in maneuver decision for emergency braking and evasive maneuvers.

The modular system design allows to combine the motion prediction with further situational knowledge, for example due to more detailed classification methods, object tracking or prediction of driver interaction. Therefore enhancements in motion modeling support an increased robustness in situation analysis and constitutive decision making.

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