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Situational Assessments Based on Uncertainty-Risk Awareness in Complex Traffic Scenarios

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Abstract: Situational assessment (SA) is one of the key parts for the application of intelligent alternative-energy vehicles (IAVs) in the sustainable transportation. It helps IAVs understand and comprehend traffic environments better. In SA, it is crucial to be aware of uncertainty-risks, such as sensor failure or communication loss. The objective of this study is to assess traffic situations considering uncertainty-risks, including environment predicting uncertainty. According to the stochastic environment model, collision probabilities between multiple vehicles are estimated based on integrated trajectory prediction under uncertainty, which combines the physics- and maneuver-based trajectory prediction models for accurate prediction results in the long term. The SA method considers the probabilities of collision at different predicting points, the masses, and relative speeds between the possible colliding objects. In addition, risks beyond the prediction horizon are considered with the proposition of infinite risk assessments (IRAs). This method is applied and proved to assess risks regarding unexpected obstacles in traffic, sensor failure or communication loss, and imperfect detections with different sensing accuracies of the environment. The results indicate that the SA method could evaluate traffic risks under uncertainty in the dynamic traffic environment. This could help IAVs' plan motion trajectories and make high-level decisions in uncertain environments.

Keywords: intelligent alternative-energy vehicles; situational assessments; uncertainty-risk awareness; infinite risk assessments

1. Introduction

Intelligent alternative-energy vehicles (IAVs) have received extensive research interest because they show great potential for use in more efficient, safer, and cleaner transportation systems [1,2]. Developments in this field will evidently increase in both quality and importance over time [3]. Situational assessment (SA) is one of the indispensable parts for IAVs to understand the environment especially in complex traffic scenarios. The work of SA is to perceive the elements in the environment, comprehend their meanings, and project their statuses in the near future [4]. With the improvement of SA, IAVs could make better decisions and commands to actuation systems such as the brake-by-wire system [5,6]. In SA, it is crucial to be aware of uncertainty-risks, such as sensor failure and communication lossl, because no sensor exists that is noise free. In other words, there is no system with one hundred percent reliability of perception. Therefore, uncertainty should be considered and analyzed to deal with different qualities of detecting in the SA or decision making for the safety of IAVs. Moreover, one of the great developments for automotive technologies is the vehicle communication technology, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication technologies [7]. These make it easier to acquire accurate and abundant traffic information, which could improve safety and efficiency of transportation networks. However, uncertainties, such as the communication loss and sensing noises, could not be denied to develop IAVs.

Take the intersection scenario shown in Figure 1 as an example, a simplified scenario where a traffic accident happened once [8]. There were two vehicles in this scenario. The red one was an automated vehicle and the white one was a truck in the surrounding environment. It is shown that the white truck would turn left and the red vehicle kept its direction. During this interaction, there were some intervals that the perception systems failed to detect with the white truck. In this example, it is crucial that the red vehicle has to be aware of the uncertainty during the failure of sensing. Otherwise, the red vehicle might not have enough time to respond when it realizes that the truck is approaching it, which could result in a traffic accident.

Figure 1. An intersection scenario when sensors failed.

Nowadays, most of the research on IAVs is focusing on energy efficiency [9], improving the safety in the lower level [10], increasing the detecting accuracy [11], and enhancing the reliability of communication. In this study, the focus is about SA models considering uncertainty to ensure the safety of IAVs. There are several methods and research to deal with SAs, including uncertainties in traffic environments. The common risk assessment models are based on defining risk functions according to dynamic features, such as time to collision (TTC) and time to lane (TTL) [12]. Machine learning methods, such as support vector machine and decision trees [13], were always used extensively for projecting, since they could deal with nonlinear problems with multiple features. Even the reinforcement learning method was employed to learn the risk assessment model [14]. However, these methods did not take future potential risks or uncertainties into consideration. In addition, there have been some efforts expended on the uncertainty, as well as the environment prediction [15], but they failed to assess risks for a long term or risks beyond the prediction horizon for IAVs.

The objective of this study is to assess situational risks considering uncertainties as shown in Figure 2. In this study, an SA method is proposed based on considering uncertainty risks including environment predicting uncertainty. Based on the stochastic environment model, collision probabilities between multiple vehicles are estimated on the basis of integrated trajectory prediction, which combines the physics- and maneuver-based trajectory prediction models for accurate prediction results in the long term. The SA method considers the probabilities of collision at different predicting points, the masses, and relative speeds between the possible colliding objects. In addition, risks beyond the prediction horizon are considered with the proposition of infinite risk assessments (IRAs). This method is applied and proved to assess risks regarding unexpected obstacles in the traffic, sensor failure or communication loss, and the imperfect detection of the environment.

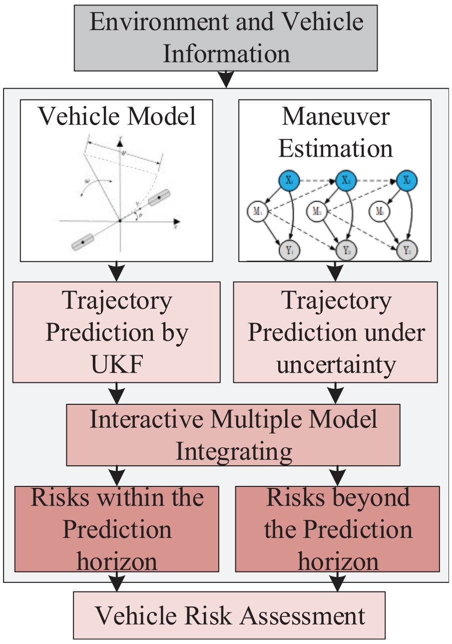

Figure 2. The structure of the situational assessment (SA) based on uncertainty-risk awareness.

The reminder of this paper is organized as follows: Section 1 introduces the related work pertaining to SA models. Section 2 presents the collision assessment under traffic environment prediction and uncertainty awareness. Section 3 presents the risk assessment, including the collision risk assessment during the prediction horizon and the risk assessment beyond the prediction horizon. In Section 4, the application of the uncertainty-risk awareness methods in different scenarios, namely unexpected obstacles, sensor failure or communication loss, and the imperfect detection with different sensing accuracies of the environment, will be introduced. In addition, the results will be described and analyzed. Finally, Section 5 presents some conclusive remarks.

2. Related Work

As mentioned previously, SAs based on uncertainty-risk awareness are crucial for the research on the application of IAVs in the sustainable transportation. Therefore, many research efforts have been expended on SAs for the safety of intelligent vehicles in different scenarios, such as lane-changes [13] and intersections [16].

The common risk assessment models are based on defining risk functions according to dynamic features, such as time to collision (TTC) and time to lane (TTL). These common risk assessment models are called dynamic feature-based models. Dynamic feature-based models project vehicle dynamic parameters, such as the relative velocity, distance, and lateral acceleration, onto risk assessments. In [17], it was indicated that TTC was just effective for a time horizon on a straight road. TTC would become less efficient as a risk indicator in complex situations such as intersections. In addition, machine learning methods, such as support vector machine and decision trees, were always used extensively for projecting, since they could deal with nonlinear problems with multiple features [13,18]. Moreover, the inverse reinforcement learning method was employed to learn the risk assessment model from driving demonstrations [14]. Some complex mathematic models were proposed considering dynamic features, such as the safety field model [19]. These models firstly defined the relationship between features and SA models and then calibrated the parameters of the function using realistic driving data [20]. The driving safety model was used and proved in the pre-collision warning system. Furthermore, in [21], a potential field consisting of different types of energy functions was used to assess the risk and make decisions for autonomous vehicles. However, these methods did not take future potential risks or uncertainties into consideration.

Some methods have been employed to deal with the uncertainty in the dynamic feature-based models. In [22], Ward et al. developed the extending TTC in general traffic scenarios, which considered the uncertainty of communication loss to evaluate the collision likelihood. In [23], a probabilistic estimation of the risk based on the Hybrid-Sampling Bayesian Occupancy Filter framework was proposed. However, these methods did not consider the future environment changing or the collision cost. With the aim to consider the potential risks in the future, the predicted vehicle positions and the relative distances were used to compare with the safe threshold and predict the collision risk in [24]. However, the uncertainty from the sensing and predicting positions was not included in this research. In addition, risks based on detecting unusual events and conflicting maneuvers were mentioned and surveyed in [25].

Some research has been focused on dealing with the future potential risks by predicting traffic environments under uncertainty. In [26], Lee et al. proposed a collision prediction model and monitoring algorithm for collision avoidance within black zones by considering the location uncertainty of moving vehicles. A solution for 3D collision avoidance on a low-cost UAV using the velocity obstacle approach was presented in [27]. This research dealt with detecting uncertainties from sensors. The To Goal (TG) heuristic and Maximum Velocity (MV) heuristic were used for the UAV's trajectory to the goal. In [16], the authors predicted the probability of a collision considering the ego vehicle trajectory and the predicted trajectory in the planning and prediction horizon, which was applied in the intersection scenarios. In [15], Laugier et al. used the on-board sensors to analyze and interpret the dynamic scenes, and the collision risks were estimated by dealing with uncertainties from sensors. The collision risks were predicted with the use of hidden Markov models and Gaussian processes. However, these methods did not mention the probability or risk of collision beyond the prediction and planning horizon. In [17], the authors proposed a system called dead reckoning with dynamic errors (DRWDEs), which could forecast the future trajectory during unavailable sensing measurements. In this system, Kalman filters (KFs) with interactive multiple models (IMMs) were employed to deal with the dynamic noise covariance matrix and obtained more accurate predicting results. However, this system did not consider maneuvers for the long-term prediction. Furthermore, it did not indicate the risk of the uncertainty during unavailable sensor measurements.

3. Collision Assessments under Prediction and Uncertainty

In this section, the collision probability between vehicles is assessed based on the trajectory prediction under uncertainty. In this study, the proposed integrated trajectory prediction model is employed, which combines the physics- and maneuver-based trajectory prediction models using interactive multiple models (IMMs) [28]. It could ensure the prediction accuracy in the short term and keep the right predicting trend in a higher level for the long-term prediction. The initial information, including parameter uncertainties, could be estimated from the tracking algorithms, such as unscented Kalman filters (UKFs) [22] and extended Kalman Filters (EKFs) [29]. In this section, the environment model will be introduced firstly. Then, the collision probability based on trajectory prediction will be presented in detail.

3.1. Environment Models

In order to assess the traffic environment, a model of the traffic environment is necessary to represent the current and future states of the objects [30]. There are three kinds of environment models, namely deterministic, bounded uncertainty, and stochastic models, which are shown in Figure 3. The deterministic model represents all of the objects in the environment with no uncertainty. In other words, the current and predicting states of objects are noise-free. The bounded uncertainty model considers the uncertainty as the exact bound. This model could ensure the safety but is conservative to represent the environment. In the stochastic model, the uncertainty is represented by a probabilistic model, usually expressed as probabilistic density functions (PDFs), such as Gaussian distributions. In this study, the traffic environment is represented as the stochastic model.

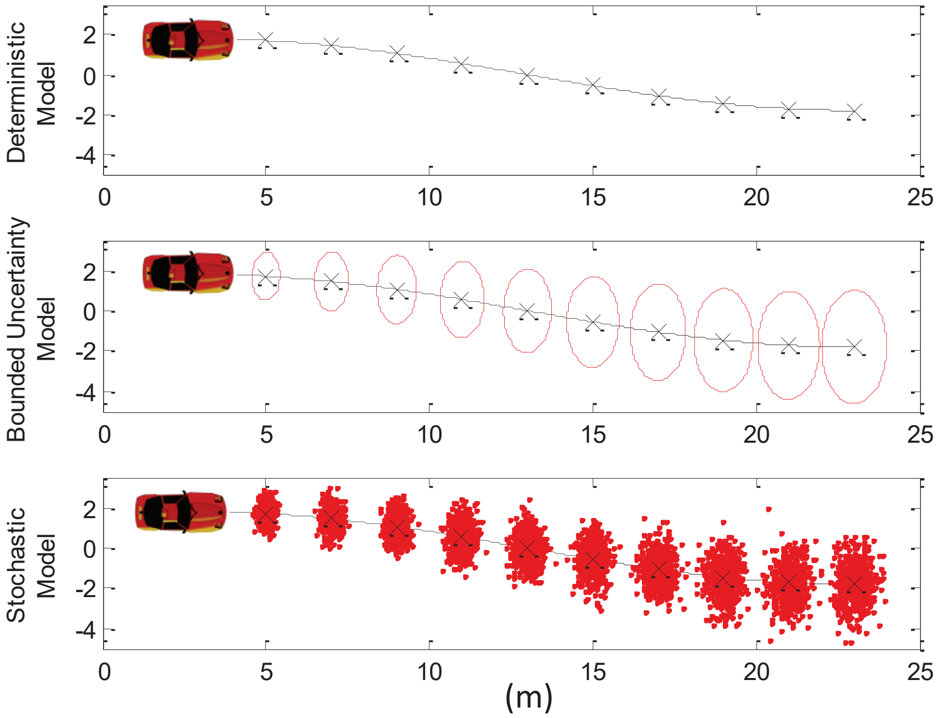

Figure 3. Different representations of environment models, including deterministic, bounded uncertainty, and stochastic models. The deterministic model represents all of the objects in the environment with no uncertainty. The bounded uncertainty model considers the uncertainty as the exactly bound. In addition, in the stochastic model, the uncertainty is represented by a probabilistic model.

The state of the vehicle is represented as $X = [x, y, v, \theta, \omega, a]$, in which $[x, y]$ is the position of the vehicle, v is the velocity in the running direction, θ is the yaw angle, ω is the yaw rate, and a is the acceleration in the driving direction. The occupancy of the vehicle at time t is expressed as $O(X(t))$. The uncertainty of the states can be represented as the probabilistic distribution $p_i(X(t_0), t), t \geq t_0$, in which t_0 is the initial time, i means the *ith* object in the traffic environment. It is defined that $i = 0$ means the ego vehicle. In other words, $p_0(X(t_0), t), t \geq t_0$ means the planning of the ego vehicle. As for trajectory planning, the trajectory of ego vehicle is assumed to be deterministic. $D(t_0) = [p_0(X(t_0), t_0), \cdots, p_N(X(t_0), t_0)]$ is the initial probabilistic distribution via sensor tracking, in which N is the number of considered objects in the traffic environment. The initial state estimations could be accomplished by filtering algorithms, such as extended Kalman filters (EKFs) and unscented Kalman filters (UKFs). The probabilistic distribution of the vehicle's future state could be predicted and expressed as follows:

$$p_i(X(t_0), t) = f_i(X(t_0), t), t \in [t_0, t_0 + T_p], \tag{1}$$

where f_i is the prediction function based on the latest detecting results $X(t_0)$, and T_p is the prediction horizon. The prediction function f_i that integrates the physics- and maneuver-based prediction approaches is introduced and researched in detail in [28].

In the curving road, it is more complex to achieve the prediction and planning using the Cartesian coordinate system. Therefore, the curvilinear coordinate system can be employed in the curving road to use the SA framework proposed in this study. In the curvilinear coordinate system, longitudinal axis is denoted along the curvature of the road and lateral axis the orthogonal direction, which was described and employed in [31]. Furthermore, the transformation of these two coordinate systems could be computed using the coordinate transformation function.

3.2. Collision Probability Based on Trajectory Prediction

The collision probability of two vehicles (V_i, V_j) in the traffic scenario could be represented as $P(C_{V_i,V_j})$. Furthermore, collision assessments based on trajectory prediction of two vehicles at a specific time point within the prediction horizon can be expressed as follows:

$$\mathrm{P}\left(C_{V_i,V_j}(t)\right) = \iint \mathrm{C}\left(b_{V_i}(t), b_{V_j}(t)\right) p_i\left(b_{V_i}(t)\right) p_j\left(b_{V_j}(t)\right) db_{V_i} db_{V_j}, \quad \mathrm{t} \in \left[t_0, t_0 + T_p\right], \tag{2}$$

where V_i presents the vehicle i, t is the time, $b_{V_i}(t)$ is the predicting position of V_i at time t, and $p_i(b_{V_i}(t))$, $p_j(b_{V_j}(t))$ is the position probability of the vehicle i, j. t_0 is the start predicting point, T_p is the predicting horizon time, and $C(b_{V_i}(t), b_{V_j}(t))$ is the collision index expressed as the following equation, which considers the shape of vehicles:

$$\mathrm{C}\left(b_{V_i}(t), b_{V_j}(t)\right) = \begin{cases} 1, O\left(b_{V_i}(t)\right) \cap O\left(b_{V_j}(t)\right) \neq \varnothing, \\ 0, else, \end{cases} \tag{3}$$

where $O(b_{V_i}(t))$ means the area that the vehicle i covers.

3.3. Collision Probability for Planned Maneuvers and Trajectories

In this study, the collision probability for the planned maneuvers is assessed during the prediction horizon. The maneuvers are abstract representations of vehicle motions and could be modeled as probabilistic distributions via Gaussian processes (GPs) [32]. GPs could represent maneuvers in a probabilistic manner as continuous functions.

In the aspect of planned trajectories, which means the trajectory of V_0 could be planned deterministically, the collision assessment at a specific time point can be represented as follows:

$$\mathrm{P}\left(C_{V_i,V_0}(t)\right) = \int \mathrm{C}\left(b_{V_i}(t), b_{V_0}(t)\right) p_i\left(b_{V_i}(t)\right) db_{V_i}, \quad \mathrm{t} \in \left[t_0, t_0 + T_p\right]. \tag{4}$$

4. Risk Assessments

Strategies or decisions made by vehicles in general are trying to minimize the payoff rather than the collision probability for the reason that not all possible collisions regarding uncertain environments are equal with respect to collision risks. Some collisions would be happened in the near future with more risks and sometimes the collision regarding uncertain environments are equal respect to collision risks. In this study, risks of the collision consider the collision time, the mass of vehicles, as well as the relative velocity. In this section, the risk assessment within the prediction horizon will be introduced firstly. Then, the risk beyond the prediction horizon will be assessed.

4.1. Risk Assessments within the Prediction Horizon

Based on the trajectory prediction, the risk could be assessed by taking the consideration of the collision time, the mass of vehicles, as well as the relative velocity.

Therefore, the risk function at a specific predicting time point could be expressed as follows:

$$\mathrm{Risk}_{\mathrm{in}}\left(V_i\left(t\right), V_j\left(t\right)\right) = \mathrm{P}\left(C_{V_i,V_j}\left(t\right)\right) cost_{coll}\left(t\right), \quad \mathrm{t} \in \left[t_0, t_0 + T_p\right], \tag{5}$$

where $Risk_{in}(V_i(t), V_j(t))$ is the risk at the predicting point t, and $cost_{coll}\left(t\right)$ is the cost function with respect to the collision. The cost function $cost_{coll}\left(t\right)$ could be expressed as follows:

$$cost_{coll}\left(t\right) = \frac{1}{2}\frac{m_i m_j}{m_i + m_j}\left\|v_r\left(t\right)\right\|^2 \frac{1}{t_p}, \tag{6}$$

where m_i is the mass of object i, m_j is the mass of object j, $v_r(t)$ is the relative velocity of the two vehicles, t is the assessment time, and $t_p = t - t_0$. $E = \frac{1}{2}\frac{m_i m_j}{m_i + m_j}\left\|v_r\left(t\right)\right\|^2$ is called the internal energy [30].

Therefore, the risk assessment between two vehicles within the prediction horizon represented as $\mathrm{Risk}_{\mathrm{in}}\left(V_i\left(t_0 : t_0 + T_p\right), V_j\left(t_0 : t_0 + T_p\right)\right)$ can be expressed as the collision prediction distribution over the future time span:

$$\mathrm{Risk}_{\mathrm{in}}\left(V_i\left(t_0 : t_0 + T_p\right), V_j\left(t_0 : t_0 + T_p\right)\right) = \int_{t_0}^{t_0 + T_{max}} \frac{1}{2}\frac{m_i m_j}{m_i + m_j}\left\|v_r\left(t\right)\right\|^2 \mathrm{P}\left(C_{V_i,V_j}\left(t\right)\right)\frac{1}{t_p}dt, \tag{7}$$

$$T_{max} : \mathrm{P}\left(C_{V_i,V_j}\left(T_{max}\right)\right) = \max_{t \in \left[t_0, t_0 + T_p\right]} \mathrm{P}\left(C_{V_i,V_j}\left(t\right)\right). \tag{8}$$

In complex traffic scenarios, the risk assessment should be considered in multiple vehicles. The risk assessment of the vehicle V_i in a scene S_i could be expressed as follows:

$$\mathrm{RA}_{\mathrm{in}}\left(V_i, S_i\right) = \max_j\left(\mathrm{Risk}_{\mathrm{in}}\left(V_i\left(t_0 : t_0 + T_p\right), V_j\left(t_0 : t_0 + T_p\right)\right)\right), \tag{9}$$

where S_i presents the scene i, and V_i, V_j are the vehicles in the scene.

4.2. Risk Assessments beyond the Prediction Horizon

Although the risk could be assessed based on the trajectory prediction in the prediction horizon, the risk beyond the prediction horizon may end in a collision immediately. This is shown in Figure 4. In this figure, Vehicle A is approaching Vehicle C in the middle lane. Furthermore, there is a slow vehicle (Vehicle B) in the left lane. Within the prediction and planning horizon, Vehicle A may change into the right lane. Therefore, without risk assessments beyond the prediction horizon, Vehicle A will approach a road bottleneck. As a result, Vehicle A has to decrease to a slow speed. This indicates that the risk beyond the prediction horizon should be considered in SA and decision making.

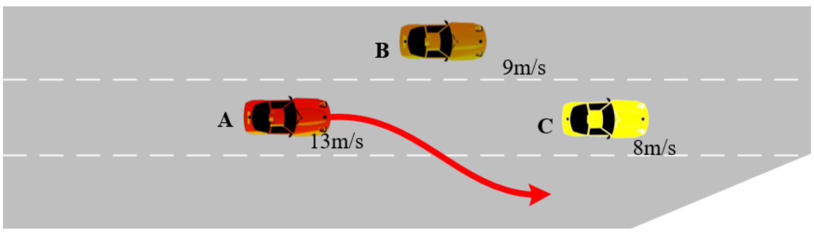

Figure 4. Without the risk assessment beyond the prediction horizon.

In this study, the risk beyond the prediction horizon is assessed as follows:

$$\mathrm{RA}_{\infty}\left(V_i, S_i\right) = \int \mathrm{P}\left(\mathrm{t}\right) \mathrm{I}\left(V_i, S_i, m_t^i\right) \frac{1}{2} \frac{m_i m_j}{m_i + m_j} \|v_r\left(t\right)\|^2 dp, \tag{10}$$

where $\mathrm{RA}_{\infty}\left(V_i, S_i\right)$ is the risk beyond the prediction horizon called IRAs, and $I(V_i, S_i, m_t^i)$ is defined as follows:

$$\mathrm{I}\left(V_i, S_i, m_t^i\right) = \begin{cases} \frac{\Delta v}{\Delta d}, & if \frac{\Delta v}{\Delta d} > 0, \\ 0, & if \frac{\Delta v}{\Delta d} \leq 0, \end{cases} \tag{11}$$

where Δv and Δd are the predicted relative velocity and distance between the vehicle i and j.

4.3. Integrated Risk Assessments Using Gaussian Distributions

In this study, the SA could be expressed as the integrated risk assessments combining risk assessments within and beyond the prediction horizon. The integrated risk assessment $RA(V_i, S_i)$ for the vehicle V_i in the scene S_i could be expressed as follows:

$$\mathrm{RA}\left(V_i, S_i\right) = \mathrm{RA}_{in}\left(V_i, S_i\right) + \mathrm{RA}_{\infty}\left(V_i, S_i\right). \tag{12}$$

In this study, the uncertainty of the environment is assumed as the Gaussian distribution $\mathcal{N}$. As a result, the state of vehicles in the traffic at a certain time point could be expressed as follows:

$$X\left(t\right) \sim \mathcal{N}\left(\mu\left(t\right), \Sigma\left(t\right)\right), \tag{13}$$

where $\mu\left(t\right)$ is the predicting states for vehicles and $\Sigma\left(t\right)$ is the covariance matrix for the predicting uncertainty.

On the basis of historical sensing and tracking results from sensors, the traffic environment could be predicted under uncertainty. In the predicting horizon T_p, the predicting results could be expressed as follows:

$$\left\{X\left(t+1\right), X\left(t+2\right), \cdots, X\left(t+T_p\right)\right\}. \tag{14}$$

As a result, the integrated risk assessment could be obtained according to Equation (12). In this study, the predicting of other vehicles is based on combining the physics- and maneuver-based approaches as shown in Figure 2, which could both ensure the predicting accuracy in the short term and keep the running trend in the long term. When on-board sensors fail or the communication gets lost during some intervals, the predicted results could be used to update as the information is available. The difference is that the covariance of the predicted information could be larger than that from sensors or communication devices.

In this study, the integrated risk assessment could model the risk of the unexpected obstacles in the traffic. It is assumed that the unexpected obstacles move in typical patterns [33]. For example, the unexpected pedestrian crossing the road is supposed to move along the crossing pattern. The probability of the unexpected obstacle appearing in the traffic scene P_u could be expressed as a homogeneous Poisson process as follows:

$$P_u\left(N_k\left(t_1\right) - N_k\left(t_0\right) \geq 1\right) = 1 - e^{-\lambda_k \tau}, \tag{15}$$

where $(t_0, t_1]$ is the time interval, $\tau = t_1 - t_0$, $N_k(t_1) - N_k(t_0) \geq 1$ means that the number of unexpected obstacles is at least one during the time interval, λ_k is the rate parameter which means that the expected number of obstacles per unit of time, and k represents a type of pattern. This means that a different parameter λ_k could be chosen according to each typical pattern k. The rate parameter could be obtained on the basis of observations in different places or times in a day/week.

5. Uncertainty Analysis in Application Scenarios

In this study, the SA based on uncertainty-risk awareness is applied and proved in three scenarios, namely SAs regarding unexpected objects, sensor failure or communication loss, and imperfect sensing with different accuracies. In this section, the scenarios will be introduced briefly and then the results for SAs with uncertainty will be analyzed and discussed in detail.

5.1. Situational Assessments Regarding Unexpected Objects

In the traffic environment, especially in the urban area, it is common that unexpected objects, such as pedestrians, might appear because of the imperfect perception in undetectable areas. One example is shown in Figure 5. In this figure, there are three vehicles, namely Vehicle A, Vehicle B, and a white truck. In this scenario, the white truck is parking on the right side of the road, which makes it difficult for Vehicle A to detect the moving obstacles ahead, such as pedestrians crossing the road. However, in the near future, it is possible that Vehicle A might crash into a pedestrian in the undetectable area. It is more dangerous if Vehicle A moves faster. With the forward of Vehicle A, it becomes more confident whether there is a pedestrian crossing the road or not. This scenario is common in the urban traffic environment.

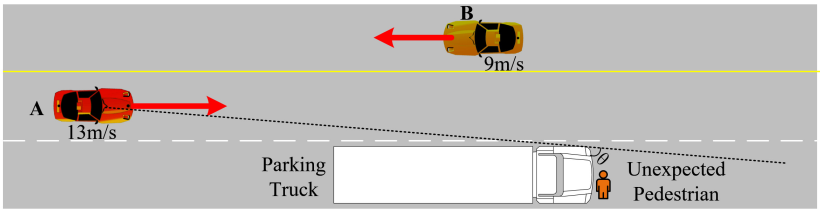

Figure 5. The scenario regarding unexpected objects.

In this scenario, even there is no pedestrian ahead of the white truck crossing the road in reality, Vehicle A has to evaluate the risk of possible crossing pedestrians in the undetectable area.

In this study, the probability of the pedestrian appearing in each interval is expressed as Equation (15). As a result, at each predicting point, the collision risk could be expressed as

$$\text{Risk}_u\Big(V_i\,(t)\,,V_j\,(t)\Big) = P_u \cdot \text{Risk}_{\text{in}}\Big(V_i\,(t)\,,V_j\,(t)\Big), \tag{16}$$

where $\text{Risk}_u\,(V_i\,(t)\,,V_j\,(t))$ is the collision risk regarding unexpected pedestrians at the predicting time point t, P_u is the appearing probability of unexpected pedestrians, and $\text{Risk}_{\text{in}}\,(V_i\,(t)\,,V_j\,(t))$ is the collision risk when there is a pedestrian crossing.

With the fact that Vehicle A is approaching the parking white truck, the view field of Vehicle A is changing. Therefore, the undetectable area will become smaller and the start-crossing point of unexpected pedestrians will become farther in the lateral direction. In this scenario, the start-crossing point could be expressed as follows:

$$l_s = l_o + w \cdot \cot\theta, \tag{17}$$

where l_s is the lateral distance between the start-crossing point and Vehicle A, l_o is the lateral distance between the parking white truck and Vehicle A, w is the width of human beings, and θ is the angle of the undetectable area as shown in Figure 5.

The speed planning of Vehicle A is assumed to be constant, and Vehicle A keeps itself in the middle of the lane. In order to make it simple to compare the results, the invariable parts in the SA are assumed to be one unit which equals to 1. Furthermore, this is also applied to the other scenarios in this study. By considering these facts, the risk in this scenario are shown in Figures 6 and 7.

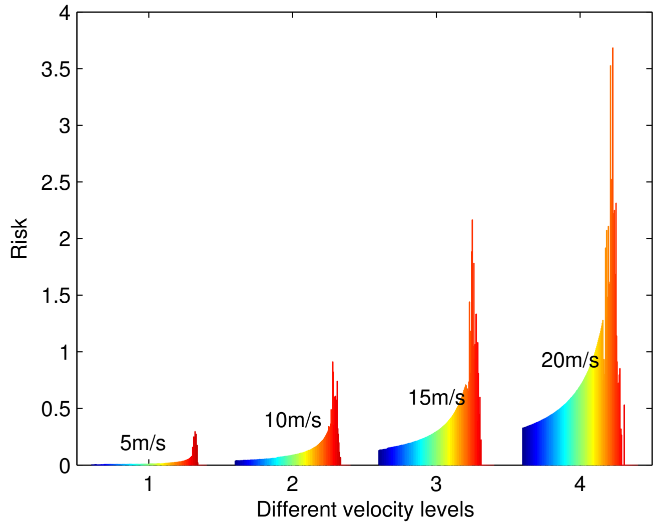

Figure 6. Risk assessments with different vehicle velocity levels regarding the unexpected pedestrian.

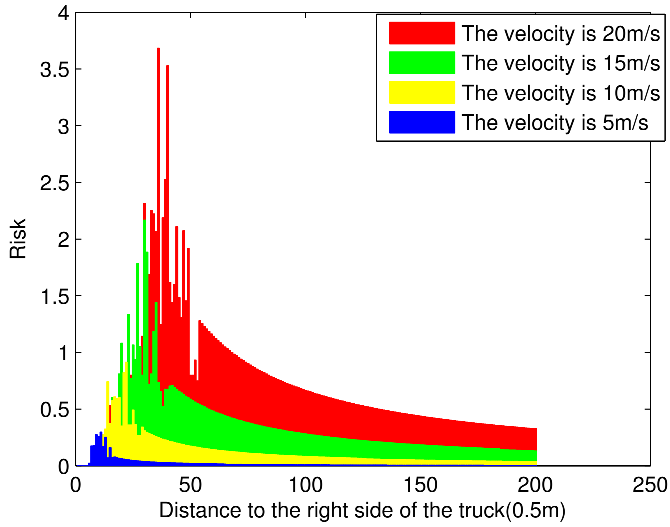

Figure 7. Risk analyzing with the distance to the right side of the truck.

The results in Figure 6 indicate that risks regarding the unexpected pedestrians in this scenario increase with the planning velocity of the vehicle. This corresponds to our everyday driving experiences. When we come across a big truck parked aside, the higher velocity is, the more risks we might feel with considering unexpected pedestrians happening to cross. To analyze the risks with the distance to the right side of the truck, the results in Figure 7 show that risks regarding the unexpected pedestrians are increasing when Vehicle A approaches the right side of the truck far away; then the risks reach the maximum. After this, the risks of the unexpected pedestrians decrease, since the undetectable area is becoming small. Also, when the planning speed becomes decreased, the risks decrease and the maximum risk point is closer to the right side of the truck. This also corresponds to the everyday driving experience.

5.2. Situational Assessments Regarding Sensor Failure or Communication Loss

In this study, it is assumed that vehicles in the connected traffic broadcast the state and the related uncertainty information to other vehicles or the cloud [22]. If communications get lost or sensors fail in a certain time, the prediction results are employed as the lasted initial states and distributions for trajectory predictions. When communications or sensors get reestablished after a short time of loss, estimated results, including uncertainty information from detecting signals, are used as the latest initial states.

In this section, the SA regarding sensor failure or communication loss is applied in the lane keeping and lane changing scenarios, which are shown as Figures 8 and 9. In these two figures, there are two vehicles running on the right side, and Δt_{loss} means the time in which the sensor fails or communication is lost. Before the sensor failure or communication loss, the probabilistic distribution of maneuvers could be estimated as the initial maneuver distribution on the basis of dynamic Bayesian networks. The initial maneuver distribution could be expressed as follows:

$$P_m^0 = \left(P_1^0, \cdots, P_n^0, \cdots, P_N^0 \right), \tag{18}$$

where P_m^0 is the probabilistic distribution of maneuvers at the initial time $t = 0$, P_n^0 represents the probability of the nth maneuver, and N is the size of maneuvers.

On the basis of the first-order Markov theory, the switching probability of the maneuvers during the sensor failure or communication loss could be expressed as follows:

$$P_m^k = M \left[P_m^{k-1} \right]^T, \tag{19}$$

where P_m^k is the maneuver probabilistic distribution at step k of the sensor failure or communication loss, and M is the probability switching matrix.

Therefore, the risk during the sensor failure or communication loss could be estimated as

$$\mathrm{RA}_k \left(V_i, S_i \right) = \sum_{n=1}^{N} P_n^k \mathrm{RA}_k \left(V_i, S_i | m_j = n \right), \tag{20}$$

where $\mathrm{RA}_k \left(V_i, S_i \right)$ is the risk at step k of the sensor failure or communication loss, N is the size of maneuvers of Vehicle j, and $\mathrm{RA}_k \left(V_i, S_i | m_j = n \right)$ is the risk when the maneuver of Vehicle j is $m_j = n$.

In the lane keeping scenario as shown in Figure 8, Vehicle A could not acquire any information about Vehicle C during the information loss time Δt_{loss}. As a result, Vehicle A could only assess the situation using historic information, and the predicted results are used as the updating information at every time step.

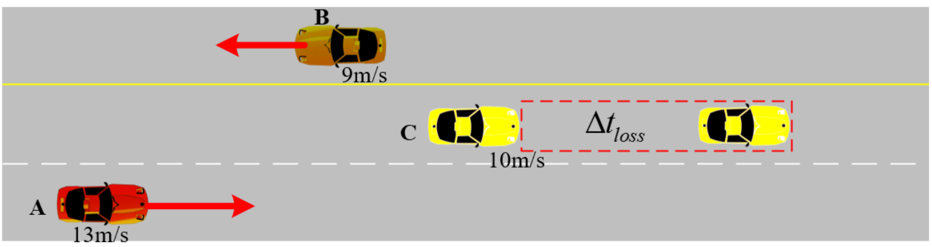

Figure 8. The scenario regarding sensor failure or communication loss in the lane keeping scenario.

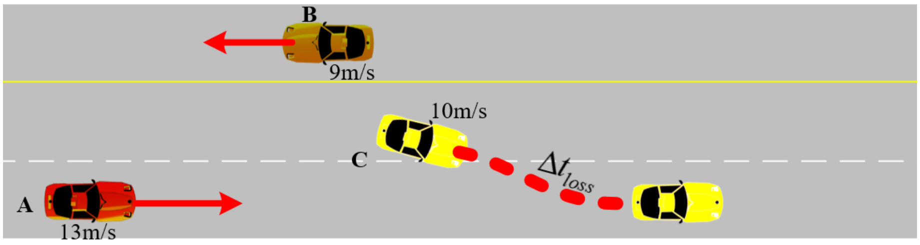

Figure 9. The scenario regarding sensor failure or communication loss during lane changing.

The risks regarding the sensor failure or communication loss in the lane keeping scenario are shown in Figure 10. This figure shows the relationship between risks and the sensor failure or communication loss time. The results indicate that the risk increases with the duration of the sensor failure or communication loss. In the lane keeping scenario, there are some chances that Vehicle C would change its lane during the sensor failure or communication loss. In other words, the uncertainty-risk during the sensor failure or communication loss is considered in this SA. If the uncertainty-risk from the adjacent lane is ignored, this may cause serious traffic accident even if there are no vehicles in the same lane with Vehicle A.

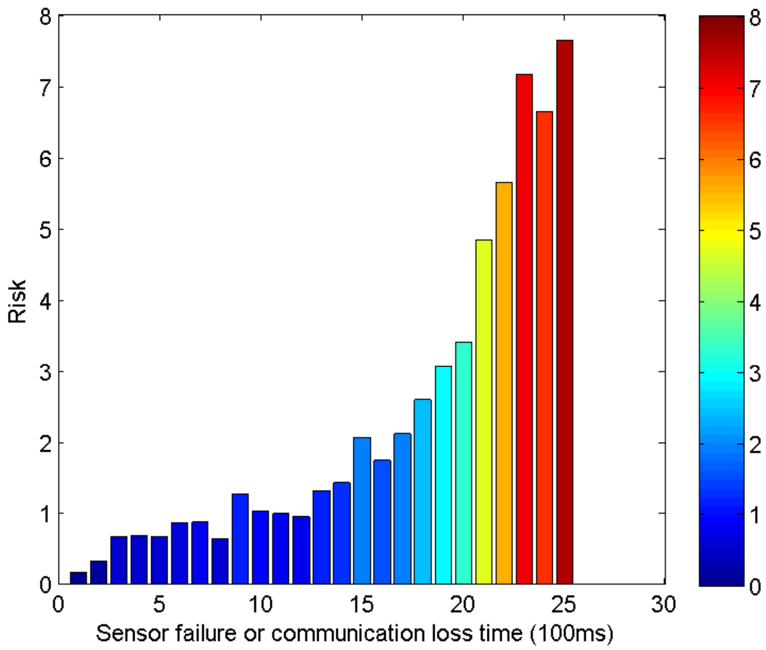

Figure 10. Risks regarding the sensor failure or communication loss in the lane keeping scenario.

In the lane changing scenario as shown in Figure 9, there is an information loss time Δt_{loss} during the lane-change. During the information loss time, the initial estimating information at every loss time step k could be replaced by the prediction results based on historic information before the information loss.

The risks regarding the sensor failure or communication loss in the lane changing scenario are shown in Figure 11. In this figure, risks considering prediction uncertainty and risks without considering prediction uncertainty during the sensor failure or communication loss are compared and analyzed. The length of the blue bars indicates the risk considering prediction uncertainty during the sensor failure or communication loss, that of red ones means the risk without considering prediction uncertainty during the sensor failure or communication loss. The comparison results indicate that the risk without considering prediction uncertainty during the sensor failure or communication loss in the lane changing scenario is smaller than that with considering the prediction uncertainty. It is more rational to take the uncertainty-risk of the prediction during the sensor failure or communication loss in the lane changing scenario [22]. As a result, the SA considering the uncertainty-risk of the prediction during the sensor failure or communication loss could more likely be aware of the risk and ensure the safety.

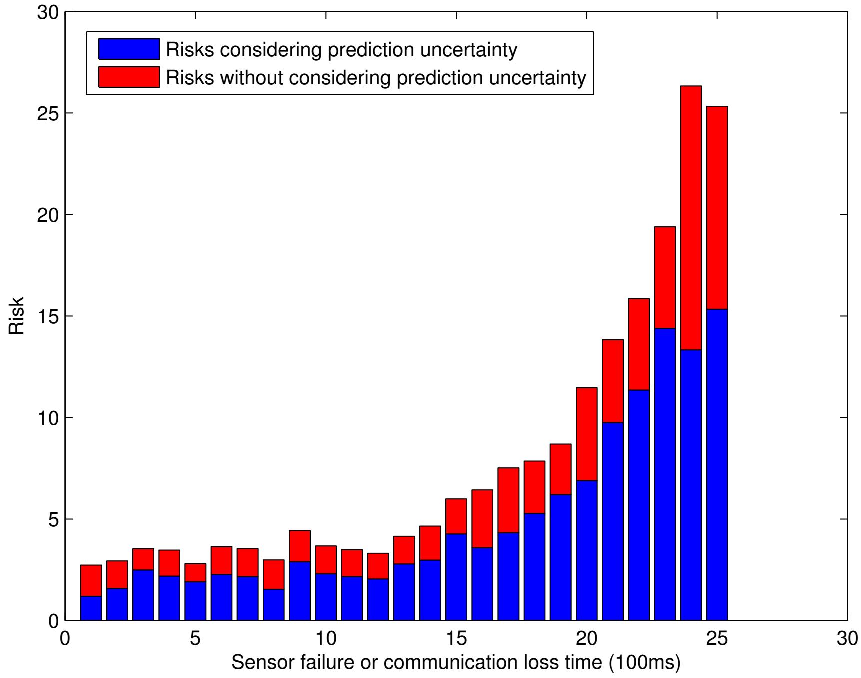

Figure 11. Risk analysis regarding sensor failure or communication loss during the lane-change.

5.3. Situational Assessments Regarding Imperfect Sensing with Different Accuracies

The SA regarding imperfect sensing with different accuracies is applied and proved in the lane-change scenario, in which vehicle C in the adjacent lane is recognized to make the lane-change using dynamic Bayesian networks [34]. The sensing information is presented by Gaussian distribution, in which the covariance could represent the degree of sensing uncertainty. For example, as shown in Figure 12, Vehicle A is the IAV and it has to be aware of the risk from Vehicle C in the adjacent lane. In one way, Vehicle A could obtain the related information about Vehicle C via platform sensors, such as the LIDAR and radar. In another way, the communication technology could be used for Vehicle C to send the related information, such as information from the differential global position system (DGPS), to Vehicle A, which has higher accuracy. It is obvious that, for Vehicle A, different sensing accuracies could cause different risks for the traffic scene. Therefore, the uncertainty-awareness risk is accessed in this study according to different sensing accuracies.

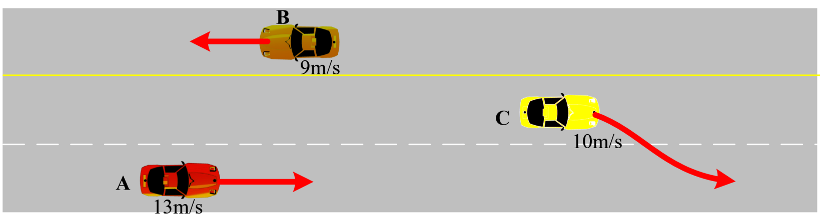

Figure 12. The scenario regarding imperfect sensing with different accuracies.

The risks regarding different detecting accuracies in the lane changing scenario are shown in Figure 13. In this figure, risks regarding high detecting uncertainty and low detecting uncertainty from different sensors are analyzed and compared. The length of red bars indicates the risks from high uncertainty detecting and that of blue ones means the risks from low uncertainty sensing. The results indicate that different sensing uncertainties could lead to different situational risks. High sensing uncertainty causes high risks with the same relative longitudinal distance between Vehicle A and Vehicle C. In other words, the SA could be aware of the sensing uncertainty-risk. This also implies that different sensor configurations for IAVs should have different decision strategies because of uncertainty risks caused by different sensing abilities.

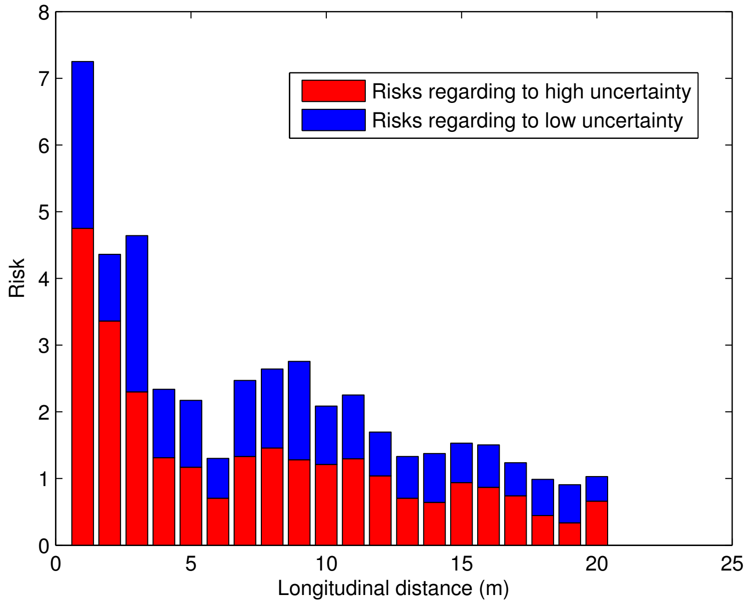

Figure 13. Risk analysis regarding different detecting accuracies.

5.4. Results and Discussion

The SA results regarding the mentioned scenarios, including unexpected objects, sensor failure or communication loss, and imperfect sensing with different accuracies, indicate that the proposed SA method based on integrated trajectory prediction could be aware of uncertainty-risks in the complex traffic environment. On the basis of the collision assessments using integrating trajectory prediction methods, the proposed SA method could deal with the risk assessments in dynamic complex scenarios rather than only car-followings compared with the TTC method. Since the uncertainty, including predicting uncertainty, is considered in the SA method, the potential and uncertain risks are exploited to ensure the safety for IAVs. This has not been discussed in the realized dynamic feature-based models, such as risk assessments using machine learning methods and driving field models via complex predefined functions. In the proposed SA method, the uncertainty-risks are mainly about sensing and predicting uncertainties, which do not consider psychosocial and driver-related variables, such as human errors and the driving fatigue discussed in [35,36]. The uncertainty-risks from the human errors and driving fatigue could be estimated by adding some other complex models, such as the driving fatigue recognition model.

6. Conclusions

This study has presented an SA method on the basis of uncertainty-risk awareness in dynamic traffic environments. Uncertainties of dynamic traffic environment perceptions and predictions were considered. In this study, risks were assessed within and beyond the prediction horizon. Within the prediction horizon, collision risks were evaluated based on the trajectory prediction under uncertainty, including the detecting uncertainty. The internal energy depending on the relative speed and the weights of colliding objects was included. In addition, risks were evaluated beyond the prediction horizon using the last prediction parameters under uncertainty. Finally, the SA method based on uncertainty-risk awareness was applied and proved in three scenarios, namely scenarios with unexpected obstacles, the sensor failure or communication loss, and imperfect sensing.

Regarding the unexpected obstacles in the undetectable area, the appearing probability of unexpected obstacles was modeled as Poisson distributions and the impact of the view-field changing was considered in the SA. Regarding the sensor failure or communication loss during the lane keeping and changing scenarios, the predicted results under uncertainty were used as the updating information to evaluate the situations. Furthermore, the possible change of maneuvers during the sensor failure or communication loss was modeled on the basis of the first order Markov theory. Finally, in order to compare the risk of different sensing accuracy, the lane-change scenario with imperfect sensing was considered. The results of the risk assessment indicate that the SA method proposed in this study could evaluate risks on the basis of the uncertainty-risk awareness and traffic environment prediction.

This study also exhibited several limitations. The interaction and gaming between multiple road users, which influence the SA for IAVs, are not considered in the proposed SA. In addition, the uncertainty-risks from the human factors, such as human errors and the driving fatigue, are not studied and included in this study. In the future work, the interactions between multiple traffic users will be considered to evaluate risks of the traffic situation using game theories. Moreover, the decision making and trajectory planning will be considered on the basis of this SA model under uncertainty and traffic environment prediction.

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