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A New Methodology for Collision Risk Assessment of Autonomous Vehicles

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ABSTRACT

Risk assessment methods of autonomous vehicles (AVs) have recently begun to treat the motion of the vehicles as dependent on the context of the traffic scene that the vehicle resides in. In most of the cases, Dynamic Bayesian Network (DBN) models are employed for interaction aware motion models (i.e. models that take inter-vehicle dependencies into account). However, communications between vehicles are assumed and the developed models require a lot of parameters to be tuned. Even with these requirements, current approaches cannot cope with traffic scenarios of high complexity. To overcome these limitations, the current study proposes a new methodology that integrates real-time collision prediction as studied by traffic engineers with an interaction-aware motion model for autonomous vehicles real-time risk assessment. Results from a random forest classifier for real-time collision prediction are used as an example for the estimation of probabilities required for the DBN model. It is shown that a well-calibrated collision prediction classifier can provide a supplementary hint to already developed interaction-aware motion models and enhance real-time risk assessment for autonomous vehicles.

Keywords: *Autonomous Vehicles, Traffic Safety, Real-time Risk Assessment, Dynamic Bayesian Network, Random Forest*

1 INTRODUCTION

2 Recent developments in computational intelligence, vehicle technology and software
3 algorithms have brought about the introduction of Autonomous Vehicles (AVs) closer to reality,
4 especially in commercial fleets. AVs are envisaged to make a profound impact on the economy,
5 mobility and society as a whole (1). Nonetheless, the most important advantage offered by AVs
6 relates to improved road safety that is promised by researchers and manufacturers worldwide (2).
7 Human drivers are responsible for a 94% of the critical pre-collision events according to a recent
8 survey from the National Highway and Traffic Safety Administration (3) while the remaining 6%
9 includes vehicle, environmental and undefined factors. A large number of traffic collisions and the
10 related casualties could, therefore, potentially be reduced by removing the human involvement from
11 the task of driving through the rapid uptake and penetration of AVs.

12 In order to ensure the safety of its occupants and other road users, an AV has to perform a
13 safe navigation when interacting with other vehicles, pedestrians and cyclists. This fundamental task
14 is known as path planning within the AV literature. Planning provides a vehicle with a safe and
15 collision-free path towards its destination while taking into account the vehicle dynamics, its
16 manoeuvre capabilities in the presence of obstacles, traffic rules and road boundaries (4). Collision
17 prediction and situational risk assessment usually takes place in the manoeuvre planning (5),
18 otherwise termed as behavioural layer (6) of current planning approaches in automated driving.

19 Currently, a motion model is used to predict the intended trajectories of other vehicles and
20 surrounding objects in a specific traffic environment and compare them with the trajectory of the
21 interested AV in order to estimate the collision risk. Computational complexity however emerges
22 when searching for an efficient trajectory representation in which vehicles are assumed to move
23 independently (7, 8). Recent approaches (7, 9, 10) try to address the problem of risk assessment of
24 AVs by taking into account contextual information (i.e. information on the traffic scene and the
25 motion of other vehicles) as well as human-like reasoning about vehicles' interaction without
26 predicting the trajectories of all other vehicles. The main method for making such predictions is the
27 use of probabilistic models, especially Dynamic Bayesian Networks (DBNs)(11) which are a robust
28 framework for drawing an inference from the vehicle dynamics and the contextual information and
29 can handle missing or erroneous data while maintaining real-time tractability (8). Nonetheless, perfect
30 sensing or communications between vehicles are often assumed (5).

31 The inherent limitations of robotics-based approaches on risk assessment in the context of
32 organically changing dynamic road environments indicate that alternative methods should be sought
33 as supplements for building a robust and comprehensive risk assessment module.

34 Over the past years the estimation of the probability of a traffic collision occurring in real-
35 time has also been studied by many researchers working in the traffic safety/traffic engineering
36 perspective of ITS. The predominant technique of evaluating collision risk is by comparing traffic
37 dynamics (e.g. speed, flow, occupancy) on a specific road segment just before a reported collision
38 with traffic measurements from the same segment and time at normal situations(12). It can be
39 understood that the traffic engineering perspective addresses the macroscopic problem of identifying a
40 location with high-risk of a collision occurrence. This spatiotemporal risk could potentially provide a
41 broader picture of the road network in terms of hazardous traffic conditions as an additional safety
42 layer to AVs. This would also reduce the computational time leading to faster identification of objects
43 deemed to be the greatest threat.

44 The incorporation of this macroscopic spatiotemporal collision risk (henceforth termed as
45 “network-level risk”) into vehicle-level risk forms the motivation of this current paper. This study
46 offers a methodological extension to existing DBN-based risk assessment of AVs with the aim of
47 enhancing their perception of the environment and easing online computations by exploiting real-time
48 safety information for the road segment on which the ego-AV travels on. Such risk assessment
49 modules can be embedded in the path or manoeuvre planning routines of autonomous vehicles,
50 assuring a safe navigation of the ego-vehicle

51 The rest of the paper is organised as follows: first, the existing literature and its main findings
52 are synthesised. An analytic description of the proposed DBN for collision risk estimation in real-time
53 is described next. This is followed by a presentation of the data needed for such an analysis and the
54 methods used to estimate the risk of a collision. The last section summarizes results from an ensemble

classifier (i.e. Random Forests) to calculate network-level risk and discusses the applicability of the proposed DBN for real-time risk assessment of AVs.

LITERATURE REVIEW

Risk assessment of AVs has been primarily addressed in the literature by different motion models. For instance, Lefèvre et al. (8) presented a detailed survey to compare and contrast recent research on traffic environment modelling and prediction and introduced several risk estimators for intelligent vehicles. According to their work, motion models are classified into three categories: (i) physics-based, (ii) manoeuvre-based and (iii) interaction-aware models. The first category of the motion models describes according to the laws of physics while the second one relies on estimating the intentions of the other traffic participants based on either clustered trajectories or manoeuvre estimation and execution. These two categories of motion models do not take the environment into account but rather consider vehicles as independent entities. Interaction-aware motion models exploit inter-vehicle relationships as to easily identify any dangerous situations in real-time.

Because of the incorporation of contextual information when modelling the motion of the vehicles in a traffic scene, interaction-aware models with regards to risk assessment will be the focus of this literature review. It should, however, be noted that there is a dearth of research that integrate vehicle-level risk assessment with the context-aware risk assessment in order to derive a more comprehensive risk assessment of AVs (7).

As noted in the survey of Lefèvre et al. (8) the vast majority of interaction-aware motion models are built using DBN models due to their capability of handling missing data efficiently, the simplistic representation of the relationship between the variables and the real-time tractability of the model for drawing an online inference.

One of the first approaches providing a motion model taking into account traffic rules and inter-vehicle relationships along with collision risk estimation was the study by Lefèvre (9). Lefèvre pointed out that if an ego-vehicle has to predict all the future trajectories of the vehicles in its vicinity and to analyse them for any potential collisions, the whole process would become intractable for real-time applications. Her work exploited the power of interaction-aware models by the application of DBNs for the purpose of risk assessment at road intersections. Elegantly, instead of predicting the trajectories of all nearby vehicles, only vehicles which were found to disobey traffic rules or gap acceptance models were analysed for any potential collisions. It was however assumed that vehicular communications were enabled so as for the vehicles to exchange their positions, speeds and turning movements through appropriate message delivery protocols. Nevertheless, an important observation was that collision risk does not only need intersecting trajectories but also behavioural or infrastructural information in order to enhance risk estimation for AVs. In the same principle Worrall et al. (13) showed the real-time efficiency of an interaction-aware model with the aid of DBNs. They constructed a fully probabilistic model based on a DBN using an improved calculation of the Time-to-Collision (TTC) variable for risk assessment. Their approach was however failed to handle complex traffic scenarios, for instance, “give-way” at non-signalised junctions. Moreover, communications were again assumed to be available and the approach was actually tested on mining facilities which could not efficiently represent traffic dynamics on real-world road networks.

Recent approaches were formulated to better describe the traffic environment by including network-related information. Gindele et al. (10), for instance, included information on car-following models and the interactions among the vehicle in the adjacent lanes so as to faster recognise the intention of each vehicle and assessed risk using the TTC metric. Their DBN approach requires many variables which consequently need to be trained to efficiently describe, for example, the relationship between traffic participants, the influence of traffic rules to traffic participants, the influence of the geometry of the road on the actions. In order to address some of these issues, Kuhnt et al. (14) proposed to use a static street model in order to provide an extra hint to a motion model. Their approach, however, fails to provide an efficient description of the inter-vehicle dependencies. Recently, Bahram et al. (15) showed that even without vehicular communications, if the knowledge of the road geometry and traffic rules is available, the prediction time for anticipating the manoeuvres of other vehicles can be significantly improved. Nevertheless, network-level knowledge was limited to

train classifiers that have the capability of detecting any manoeuvre associated with the acceleration and deceleration of vehicles as well as lateral offsets in relation to the centre-line of a lane.

It can be concluded from the literature that interaction-aware motion models have gained attention in modelling the inter-relationship between the participants of a traffic scene explicitly. These models have also efficiently worked in real-time. It has however revealed that complex traffic scenarios are difficult to tackle and learning specific manoeuvres of the drivers and classifying them as *safe* or *dangerous* are time-consuming due to the massive datasets needed. In order to address these challenges traffic-related information is starting to become part of these motion models in the forms of car-following and gap acceptance models but the complexity of these models and the assumptions they make may hinder a comprehensive but simple representation of the traffic environment. Last but not the least, although network-level collision prediction has been researched over the years, an approach to bridge vehicle-level and network-level risk assessment is yet to be fully understood and utilised.

The overriding objective of this paper is, therefore, to address this methodological gap by extending typical DBN-formulations based on the principles of interaction-aware motion models aided by network-level collision risk prediction as an additional safety layer. The purpose is to enhance the overall risk assessment method of AVs with a particular focus on faster predictions and more comprehensive reasoning. The work builds on the previous research of Lefèvre (9) and Worrall et al. (13) which can be efficiently implemented in real-time while keeping the complexity of the DBN motion model as low as reasonably practicable.

METHODOLOGICAL BACKGROUND

The purpose of this work is to integrate network-level collision prediction with interaction-aware motion models under a Bayesian framework for risk assessment of AVs. Time-varying traffic scenes have to be modelled appropriately so that an ego-AV is able to reliably estimate the collision risk initiated by the network and surrounding vehicles as well as the interactions between the vehicles that are deemed to pose the greatest threat. Therefore, an appropriate framework for modelling dynamic systems must be applied.

Data acquisition for AVs is dependent on the temporal frequency of their built-in sensor unit. As a result, input data to the risk assessment algorithm are inherently sequential. Approaches for handling such data can be divided into two parts according to Murphy (16):

- Classical approaches such as ARIMA, ARMAX, Neural Networks and Decision Trees;
- State-space models such as Hidden Markov Models (HMMs) and Kalman Filter Models (KFMs)

State-space models outperform classical approaches in problems associated with finite-time windows, discrete and multivariate inputs or outputs and they can be easily extended (16). A known drawback of HMMs is that they suffer from high sample and high computational complexity. This means that learning the structure of the model and inferring the required probability take longer to accomplish. Furthermore, simple HMMs require a single discrete random variable which cannot cope with the description of a constantly changing environment such as a traffic scene. Factorial HMMs and coupled HMMs enable the use of multiple data streams but the former has problems related to the correlation between the hidden variables and the latter needs the specification of many parameters in order to perform an inference (11). KFMs rely on the assumption that the system is jointly Gaussian which makes it inappropriate to jointly accommodate both discrete and continuous variables (16).

In order to overcome the above limitations in handling sequential data, Murphy (16) proposed the use of DBNs. DBNs are an extension of Bayesian Networks (17) (i.e. a graphical representation of a joint probability distribution of random variables) to handle temporal sequential data. DBN representation of the probabilistic state-space is straightforward and requires the specification of the first time slice, the structure between two time slices and the form of the Conditional Probability Distribution (CPDs). A crucial part in defining a DBN is the declaration of hidden (i.e. latent) and observed variables.

When applied for the anticipation of the motion of the vehicles and risk assessment for automated driving a typical DBN layout that takes the inter-vehicle dependencies into account is shown in Figure 1a (9). The DBN requires the definition of three layers:

Layer 1: the highest level corresponds to the context of the vehicle's motion. It can be seen as a symbolic representation of the state of the vehicle (7). It can contain information about the manoeuvre that the vehicle performs (as seen in (9)) or the geometric and dynamic relationships between vehicles (as seen in (7)). The variables contained in this level are usually discrete and hidden (e.g. manoeuvre undertaken, compliance with traffic rules)

Layer 2: this level corresponds to vehicle's physical state (kinematics & dynamics of the vehicle). It usually includes information about the position, the speed and the heading of the vehicle but can accommodate information coming from a dynamic model for the motion of the vehicle (e.g. the bicycle model). The variables contained in this level are usually continuous and hidden (e.g. speed, position, acceleration)

Level 3: the lowest level corresponds to the sensor measurements that are accessible (e.g. measured speed of the ego-vehicle). The measurements are processed in order to remove noise and create the physical state subset. The variables at this level are observable.

In Figure 1a, it is noticeable that for every time moment the specific context of each vehicle influences the physical state of the vehicle and consequently the physical state is depicted on the observations from the sensors. Accordingly, it is noticeable from the thick solid arrows that the context of each vehicle at a specific time slice is dependent on the context and the physical state of every vehicle in the traffic scene at the previous time slice. This means that the probability of a vehicle belonging to a specific context in the next time slice requires the estimation of the union of probabilities which describe the context for each of the vehicles in the scene along with the probability distributions of variables related to their physical states. For more clarity, assume that an ego-vehicle is travelling in the middle lane of a motorway and senses that a lead vehicle on the left lane intends to change its lane. Based on the traffic rules, it is logical to assume that the ego-vehicle would slow down or change its lane to the right. If there is a vehicle in the right lane, then the context of "slowing-down" would have a higher probability than the context of "change its lane to the right" or "change its lane to the left" and the differences in the context would depend on the physical measurements of all vehicles in the scene (i.e. the position and speed of the ego-vehicle and the other two vehicles).

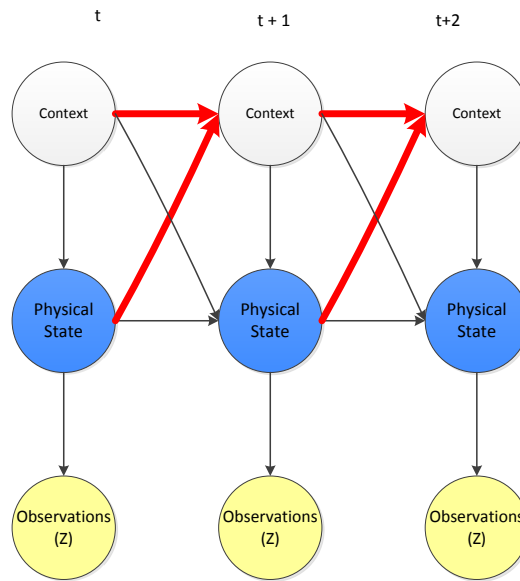
As discussed in the literature review, however, this form of DBN either is based on the assumption that vehicular communications are enabled (e.g. 11) or has problems with complex traffic scenarios (e.g. 12). To enhance risk assessment for automated driving without increasing the complexity of such DBN-based interaction-aware motion models, a new structure is proposed in this paper which introduces an additional layer described in the network-level collision prediction.

PROPOSED DBN MODEL FOR MOTION PREDICTION AND RISK ASSESSMENT

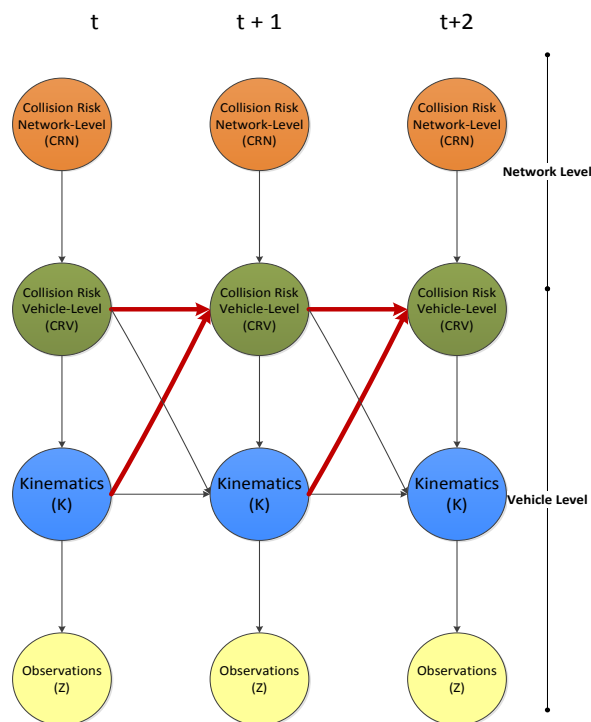
In order to include the network-level collision prediction in the motion prediction and risk assessment routine, a new layer and the corresponding dependencies of this specific layer need to be added to the model as depicted in Figure 1b.

Comparing Figures 1a and 1b it can be observed that the context layer is broken into two distinct safety-related contexts: (i) network-level collision risk and (ii) vehicle-level risk. The topology of the DBN is such in order to represent the dependencies between the layers: i) If there is safety risk on the network-level it should be depicted on the vehicle-level, ii) the vehicle-level safety level is depicted on the motion of the vehicles and iii) the motion of the vehicles is depicted on the observations from the sensors. The model presented above could, in theory, be applied to any traffic situation by defining the variables CRN, CRV, K, and Z accordingly. However, it is common knowledge that traffic data are mostly available for motorways where magnetic loop detectors and automatic vehicle identification devices exist. Therefore, the developed method is demonstrated for

the case of motorway driving. Risk assessment of AVs at junctions is not considered as an example because it has been the focus of previous research (9, 18).



a) Existing Dynamic Bayesian Networks



b) Proposed Dynamic Bayesian Network

Figure 1: Graphical representation of Dynamic Bayesian Network modelling for motion modelling and risk assessment

Variable definitions

Network-level real-time collision risk (CRN): Represents the safety context of the road segment on which the ego-vehicle is travelling on (i.e. whether the traffic conditions on the road segment are collision-prone or safe). The variable in this layer is discrete assuming two values : $\{Safe\}$ *traffic conditions, Collision-prone traffic conditions*.

As a result, (CRN_n^t) indicates the probability that the traffic conditions in the road segment (usually segments of 300-500m are used (12)) on which a vehicle n travels at time t are “collision-prone” or “safe” based on traffic dynamics. The input variables for estimating network-level collision risk consist of aggregated traffic conditions data (e.g. the mean speed of the vehicles, the mean number of the vehicles, the mean occupancy). Because many vehicles are travelling on a road segment, it is assumed that once the network-level collision risk is estimated for the segment, then its value is the same for all the vehicles in this specific segment.

Vehicle-level risk (CRV): Represents the safety context of one vehicle in a traffic scene (i.e. whether a vehicle can potentially cause a collision with the ego-vehicle). The variable in this layer is also discrete but takes four values describing the safety context of each vehicle depending on the network-level safety context: $\{Safe\}$ *driving in a road segment having safe traffic conditions, Safe driving in a road segment having collision-prone traffic conditions, Dangerous driving in a road segment having safe traffic conditions, Dangerous driving in a road segment having collision-prone conditions*.

The focus in this work is autonomous driving on motorways. “Safe” and “Dangerous” driving indicate the characterization of the manoeuvres undertaken by the vehicles in the traffic scene. Safe driving does not pose a threat to another vehicle, while dangerous driving indicates that the motion of one vehicle could be considered *unsafe* by another vehicle in the traffic.

From Figure 1(a) it can also be observed that the estimation of the vehicle-level safety context depends on the network-level safety context as well as the union of safety contexts and kinematics of all the vehicles in the vicinity of the ego-vehicle. Hence, simultaneously network-level collision prediction provides a hint to the estimation of vehicle-level collision probabilities in which the multi-vehicle dependencies are taken into account.

Sensor measurements (Z): Represents the available observations from the sensors of the ego-vehicle. Z_n^t denotes the available measurements that describe the state of the vehicle n at time t . The variables in this layer are continuous.

The measurements for each vehicle include:

$Pm_n^t = (X_n^t, Y_n^t, \theta_n^t) \in \mathbb{R}^3$: the measured lateral and longitudinal position (X_n^t, Y_n^t) and heading of the vehicle (θ_n^t)

$Vm_n^t \in \mathbb{R}$: the measured speed of the vehicles

Kinematics of the vehicles (K): Represents the physical state of a vehicle. K_n^t denotes the conjunction of all the variables that describe the physical state of the vehicle n at time t . The variables in this layer are continuous as they are referring to continuously measured quantities such as position and speed.

Based on the available measurements described previously, the following variables are selected to represent the physical state of a vehicle:

$P_n^t = (X_n^t, Y_n^t, \theta_n^t) \in \mathbb{R}^3$: the real values of the position and heading of the vehicle

$V_n^t \in \mathbb{R}$: the real value of the speed of the vehicle

Joint Distribution

For the proposed DBN depicted in Figure 1(b) the joint distribution of all the vehicles is estimated as (19):

$$\begin{aligned}
& P(\mathbf{CRN}^{0:T}, \mathbf{CRV}^{0:T}, \mathbf{K}^{0:T}, \mathbf{Z}^{0:T}) \\
&= P(\mathbf{CRN}^0, \mathbf{CRV}^0, \mathbf{K}^0, \mathbf{Z}^0) \prod_{t=1}^T \prod_{n=1}^N P(\mathbf{CRN}_n^t) \times P(\mathbf{CRV}_n^t | \mathbf{CRV}_N^{t-1} \mathbf{K}_N^{t-1} \mathbf{CRN}_n^t) \\
&\quad \times P(\mathbf{K}_n^t | \mathbf{CRV}_n^{t-1} \mathbf{K}_n^{t-1} \mathbf{CRV}_n^t) \times P(\mathbf{Z}_n^t | \mathbf{K}_n^t)
\end{aligned} \tag{1}$$

where n is the vehicle ID number in the vicinity of the ego-vehicle, t is the time moment, T is the total time duration of the measurements and N is the total number of vehicles that are observed in the traffic scene. Bold letters indicate that the indicated layers are calculated for all the vehicles. For example \mathbf{CRV}_N^{t-1} indicates the vehicle-level risk context for time $t-1$ for all the vehicles in the traffic scene.

Estimating the risk of collision using a hint from network-level risk prediction

Modelling the motion of the vehicles with regards to network- and vehicle-level risks requires a new estimation framework to be developed. In order to quantify the influence that network-level risk estimation has on estimating vehicle-level crash risk, it is essential to infer the probability that there is a vehicle-level “unsafe” situation, given the hint from the network and the measurements from the sensors.

In the majority of recent studies on network-level collision prediction (*e.g.* 19), traffic conditions at 5-10 minutes before the collision are deemed to be the most suitable to identify collision events timely and initiate an intervention by the responsible traffic agencies. However, 5-10 minute aggregation may not be suitable for the real-time safety assessment of AVs where sensor information is available at a higher sampling frequency (*e.g.* 1 Hz, 0.1 Hz). It is, however, a reality that traffic agencies aggregate traffic data at pre-defined time intervals (*e.g.* 30-second or 1-minute, 5-minute and 15-minute). Because of the difference at the temporal horizon between network-level collision prediction and vehicle-level measurements, it is assumed that the CRN layer is an observable layer. CRV and K are hidden layers because the variables in these layers are inferred through the vehicle’s sensor measurements. The sensor measurements layer (Z) is obviously an observable layer.

Exact inference in such non-linear and non-Gaussian models is not tractable. Therefore, in order to estimate the probability of a “dangerous” vehicle-level context given the traffic situation and the sensor measurements the use of particle filters (21) is proposed as they have been proven to work well in similar situations (9, 16).

If an inference algorithm is chosen, then the probability to be inferred is:

$$P([\mathbf{CRV}_n^t \in \{dCP, dSA\}] | \mathbf{CRN}_t, \mathbf{Z}_{0:t}) > \lambda \tag{2}$$

where:

- \mathbf{CRV}_n^t denotes the vehicle-level safety context of vehicle n at time t ;
- dCP, dSA denote a “dangerous” vehicle travelling on a road segment with Collision-Prone traffic conditions and a “dangerous” vehicle travelling on a road segment with SAfe traffic conditions respectively;
- \mathbf{CRN}_t denotes the network-level collision risk for all the vehicles on a specific road segment;
- $\mathbf{Z}_{0:t}$ denote the sensor measurements until time moment t ;
- λ is a threshold to identify “dangerous” encounters between the surrounding traffic participants and the ego-vehicle.

Equation 2 indicates that given a hint for the safety assessment of a road segment, the motion of the vehicles in that specific segment is affected. This resembles the fact that human drivers are also affected when the information of traffic incidents such as a broken vehicle on the roadway or a queue formation in the downstream is displayed via Variable Message Signs.

Parametric forms

In order to estimate the joint distribution of the network for inference, the functions that calculate each of the probabilistic distributions of each layer need to be defined. Due to the large number of variables for the problem and since the focus of the approach is the incorporation of network-level collision risk into existing motion models for automated driving a brief description of the parametric forms for vehicle-level risk, kinematics and sensor measurements are presented. A more analytic description of the parametric form for network-level collision risk estimation will follow along with an illustrative example for vehicle-level risk assessment.

Vehicle-level risk $P(CRV_n^t)$

The content of vehicle-level risk is derived from the previous vehicle-level risk context and kinematics of all the vehicles on the scene and is influenced by the current network-level collision prediction. The estimation of the probability that the motion of one vehicle is considered “dangerous” or “safe” is derived through a feature function that takes as input the current network-level risk, the previous vehicle-level risk context of the vehicle and the previous vehicle kinematics:

$$P(CRV_n^t | \mathbf{CRV}_N^{t-1} \mathbf{K}_N^{t-1} \mathbf{CRN}_n^t) = f(\mathbf{CRV}_N^{t-1}, \mathbf{K}_N^{t-1}, \mathbf{CRN}_n^t) \quad (3)$$

In order for this feature function to be defined three steps need to be considered:

- a) Using a Kalman Filter (11), the physical state of the vehicles in the traffic scene can be estimated. For example, after applying a Kalman Filter algorithm the elements $\{X_{ego}^t, Y_{ego}^t, \theta_{ego}^t, v_{ego}^t\}$ and $\{X_n^t, Y_n^t, \theta_n^t, v_n^t\}$ will be known. v_{ego}^t and v_n^t denote the speeds of ego-vehicle and vehicle-n respectively.

If Δp_t denotes the relative position between ego-vehicle and vehicle-n and Δv_t denotes the relative speed between ego-vehicle and vehicle n then the time-to-collision (TTC) and the distance-to-collision (δ) between the ego-vehicle and vehicle-n are expressed as follows (7):

$$\text{Time to collision: } TTC_n^t = \frac{\Delta p_t^T \Delta v_t}{\Delta v_t^T \Delta v_t} \quad (4)$$

$$\text{Distance to collision: } \delta_n^t = \sqrt{\Delta p_t^T \Delta p_t - TTC_n^t \Delta p_t^T \Delta v_t} \quad (5)$$

If $P_n^t = (X_n^t, Y_n^t, \theta_n^t)$ denote the position and heading of vehicle n at time moment t and v_n^t denotes the speed of the vehicle, an indicator function (f_K) can indicate if vehicle-n brakes dangerously, changes lane dangerously or drives safely with regard to the ego-vehicle. For rear-end crashes TTC-based thresholds could be of use (e.g. (22)):

$$f_K = f(TTC_n^{t-1}) = \begin{cases} 1: \text{dangerous if } TTC_n^t < \text{Critical TTC} \\ 0: \text{safe; otherwise} \end{cases} \quad (6)$$

- b) If a vehicle in the previous time epoch was indicated as “dangerous” in the road segment that the ego-vehicle is driving on then it is assumed that the CRV context was “dangerous”. Otherwise, it is assumed that the motion of all the vehicles was “safe”. Thus, another indicator function to take the previous vehicle-level risk of all vehicles into account can be defined as:

$$f_{CRV_N} = \begin{cases} 1 \text{ if } \sum_{n=1}^N CRV_n^{t-1} > 0 \\ 0, \text{ otherwise} \end{cases} \quad (7)$$

where N is the total number of vehicles that the ego-vehicle can sense.

- c) In order to take network-level crash risk into consideration, the network-level crash risk classification results is considered as a coefficient:

$$f_{CRN_n} = CRN_n^t = \begin{cases} 1 & \text{if } CRN: \text{dangerous} \\ 0 & \text{if } CRN: \text{safe} \end{cases} \quad (8)$$

The probability of the current vehicle-level crash risk context can now be calculated as in the following example:

$$P(CRV_n^t = "dCP \text{ or } dSA" | CRV_n^{t-1} K_n^{t-1} CRN_n^t) = \frac{\sum_{n=1}^N (f_{K_n=1}) + \sum_{n=1}^N (f_{CRV_n=1}) + \sum_{n=1}^N (f_{CRN_n=1})}{N} \quad (9)$$

where N is the total number of vehicles that the ego-vehicle can sense. It is assumed that the sampling and risk estimation frequencies will be adjusted as soon as a risk is estimated in a timestep.

Kinematics $P(K_n^t | CRV_n^{t-1} K_n^{t-1} CRV_n^t)$

The variables describing the kinematics layer must contain all the information needed in order to characterise the contexts. In this work, it was explained that the physical state vector will contain information on the position of a vehicle (in an absolute reference system, its heading and its speed. It is assumed that vehicles move according to the bicycle model (23). The kinematic bicycle model merges the left and right wheels of the car into a pair of single wheels at the centre of the front and rear axles. It is assumed that wheels have no lateral slip and only the front wheel is steerable. The equations of motion for all vehicles in the traffic scene can be integrated over a time interval Δt using a simple forward Euler integration method (24) in order to acquire the evolution of kinematics over time.

In the proposed model in Figure 1(b) and in its joint distribution as shown in equation (1) it is observed that the current kinematics depend on the previous and current vehicle-level risk context as well as on the current kinematics of the vehicle. It is assumed that vehicles moving in a specific context will follow kinematics according to that context. As a result, the parametric forms of the position, heading, and speed of each of the vehicles should be defined according to the current vehicle context and the previous kinematics only. For example:

$$P(P_n^t | CRV_n^{t-1} K_n^{t-1} CRV_n^t) = P(P_n^t | CRV_n^t K_n^{t-1}) \quad (10)$$

In order to expose the dependency of current kinematic measurements on the previous vehicle-level safety context, context-specific constraints (e.g. constraints on the TTC between ego-vehicle and another vehicle) should be defined to distinguish between contexts. For example, if the derived TTC is below 1 second this could indicate a “dangerous driving” in a road segment with safe or collision-prone traffic conditions. The parametric forms of the probability distribution of position and speed of the vehicles can be assumed to follow normal distributions (9).

For example the likelihood of the position and heading of a vehicle is defined as a tri-variate normal distribution with no correlation between x, y, and θ :

$$P(P_n^t | [CRV_n^{t-1} = C_i] [P_n^{t-1} = X_n^{t-1} Y_n^{t-1}, \theta_n^{t-1}] [V_n^{t-1} = v_n^{t-1}]) = N(\mu_{xy\theta}(X_n^{t-1} Y_n^{t-1}, \theta_n^{t-1}, C_n), \sigma_{xy\theta}) \quad (11)$$

where $\mu_{xy\theta}(X_n^{t-1} Y_n^{t-1}, \theta_n^{t-1}, C_n)$ is a function which computes the mean position and heading of the vehicle $(\mu_x, \mu_y, \mu_\theta)$ according to the bicycle model and the context-specific constraints, C_n denotes the context of vehicle-n and $\sigma_{xy\theta} = (\sigma_x, \sigma_y, \sigma_\theta)$ is the standard deviation which can be acquired from the covariance matrix of the Kalman Filter algorithm.

1 *Sensor measurements ($Z_n^t|K_n^t$)*

2
3 The sensor model used is adopted from (7) because of the use of the Student t- distribution
4 which performs better with outlier data.

5
6 The sensor model can be defined as:

$$7 \quad P(Z_n^t|K_n^t) \sim \text{Student}(C^T K_n^t, \sigma^2 I, \nu) \quad (12)$$

8 where C is a rectangular matrix that selects entries from the kinematic (physical state), ν is
9 the degrees of freedom, I is the identity matrix and σ is related to the accuracy of the sensor system.

10 11 *Network-level collision risk $P(CRN_n^t)$*

12
13 In theory, every technique which can be utilised for real-time collision prediction can be
14 applied to estimate the probability of a road segment having collision-prone traffic conditions in the
15 proposed DBN.

16 In order to use highly disaggregated data (e.g 30-seconds data), in this study traffic
17 microsimulation software (i.e. PTV VISSIM (25)) is used along with the Surrogate Safety Assessment
18 Model (SSAM) (26) which extracts conflicts using the simulated vehicles trajectories from VISSIM.
19 Furthermore, an ensemble learning classifier (i.e. Random Forests) is used for demonstration purposes
20 in this paper. A 4.52-km section of motorway M62 between junction 25 and 26 in England was used
21 as the study area. 15-minute traffic data obtained from the UK Highways Agency Journey Time
22 Database (JTDB) corresponding to every day of the years 2012 and 2013 were used as input to the
23 microsimulation software. Four simulation runs (i.e. one for identifying conflicts and three for the
24 identification of normal traffic conditions) were utilized. The number of additional runs was chosen in
25 order to cope with the imbalance between conflict and safe conditions which can prove essential for
26 classification purposes (27). The simulations were calibrated using the GEH statistic(28) and the
27 conflicts were identified in SSAM if the TTC between two vehicles was below 1.3 seconds and Post-
28 Encroachment Time (PET) was below 1 second. That is because TTC below 1.3 seconds is lower than
29 the average human reaction time (29) and PET values close to zero show imminent collisions (26).
30 For every conflict, the nearest upstream detector on the road segment was identified by comparing the
31 time of the conflict with the time the vehicles passed from every detector. This specific detector was
32 marked as “conflict detector”. Traffic data aggregated at 30-seconds intervals were extracted for every
33 conflict detector, the corresponding upstream and downstream detectors on the same lane and the
34 detector in the adjacent lane. Four simulation runs were utilized i.e.

35 In order to obtain better classification results feature selection using the information gain
36 criterion was employed in WEKA (30), before employing RF classification. The selected variables
37 were 30-second speed and number of vehicles at the “conflict-detector” and the detector in the
38 adjacent lane as well as the 30-second speed at the detector downstream of the conflict detector. The
39 classifier achieved a 78.1% overall classification accuracy with a 53.8% sensitivity and a 79%
40 specificity with the 10-fold cross-validation approach.

41 The sensitivity statistic shows the correct classification accuracy with respect to conflict-
42 prone traffic conditions, while the specificity statistic shows the classification accuracy in terms of
43 safe conditions.

44 The probability of a road segment having collision-prone traffic conditions can, therefore, be
45 estimated as:

$$46 \quad P(CRN_n^t = \text{"dangerous"}) = \left(\frac{Acc+Sen}{2}\right) * \left(\frac{TA-t}{TA}\right) \quad \text{if } CR=1 \quad (13)$$

47 where CR is the classification result for the aggregated traffic conditions in real-time (i.e. 0 or
48 1), Acc and Sen are accuracy and sensitivity of the calibrated classifier, TA denotes the temporal
49 aggregation interval (i.e. 30-seconds or 1-minute) according to the available traffic data and t is the
50 current time moment. It can be observed that if the classifier indicates a collision-prone situation then

the probability of the road segment being “dangerous” is estimated by taking into account the overall accuracy of the classifier and its performance in identifying conflict-prone conditions (i.e. sensitivity) as well as the time that has passed since the beginning of the temporal aggregation. It goes without saying that when $CR=1$ the probability of the road segment being safe is:

$$P(CRN_n^t = "safe") = 1 - P(CRN_n^t = "dangerous") \quad (14)$$

Accordingly for $CR=0$:

$$P(CRN_n^t = "safe") = \left(\frac{Acc+Spec}{2}\right) * \left(\frac{TA-t}{TA}\right) \quad (15)$$

$$P(CRN_n^t = "dangerous") = 1 - P(CRN_n^t = "safe") \quad (16)$$

where *Spec* is the specificity of the classifier (i.e. the classifier’s performance in identifying safe traffic conditions).

INFLUENCE OF NETWORK-LEVEL HINT IN VEHICLE-LEVEL RISK ASSESSMENT

In order to demonstrate how network-level hint on collision risk can be employed in real-time risk assessment for autonomous driving, an example on how to calculate the parametric forms for all the influenced variables in the proposed DBN is provided in this section.

Network-level collision risk $P(CRN_n^t)$

The classifier for the network-level collision prediction discussed in the previous section had an overall classification accuracy of 78.1% with 53.8% sensitivity and 79% specificity. If new 30-second traffic conditions are for example classified as dangerous, then at time $t=10\text{ seconds}$ after the beginning of the temporal aggregation interval:

- $CR=1$, $TA=30\text{seconds}$, $Acc=78.1\%$, $Sen=53.8\%$ and $Spec=79\%$
- According to Equation (12): $P(CRN_n^t = "dangerous") = \left(\frac{0.781+0.538}{2}\right) * \left(\frac{30-10}{30}\right) = 0.44$

As it can be understood developing a classifier with good sensitivity metric is really important in detecting conflict-prone traffic conditions because a better false alarm rate will be obtained. Furthermore, with better traffic and collision data a better accuracy can be achieved so as to enhance the safety-critical application of AVs.

Vehicle-level collision risk $P(CRV_n^t)$

Assume that the previous vehicle-level safety context is “dangerous”. Thus, according to equation (7):

- $f_{CRV_N} = 1$

Furthermore, assume that only one vehicle (i.e. vehicle-m) poses a threat to the ego-vehicle having a TTC value below the critical one as in equation (6). According to that equation:

- $f_{K-m}^t = 1$

Finally, because the network-level classification indicates collision-prone traffic conditions, according to equation (8)

- $f_{CRN_N} = 1$

If we assume that six vehicles are sensed by the ego-vehicle and all the vehicles are safe except the one mentioned previously, then the vehicle-level risk context can be acquired for the ego-vehicle according to equation (9):

$$\bullet \quad P(CRV_n^t = dCP | CRV_N^{t-1} K_N^{t-1} CRN_n^t) = \frac{\sum_{n=1}^N (f_{K_n=1}) + \sum_{n=1}^N (f_{CRV_n=1}) + \sum_{n=1}^N (f_{CRN_n=1})}{N} = \frac{1+1+1}{6} = 0.5$$

Kinematics $P(K_n^t | CRV_n^{t-1} K_n^{t-1} CRV_n^t)$

According to equation (1), the function $\mu_{xy\theta}$ needs to be defined according to context-specific thresholds and the bicycle model. Assume that the previous safety context for a vehicle is *dangerous* and driving on a *dangerous road segment*. Because the road segment is estimated as having *collision-prone* traffic conditions, the thresholds for detecting potential “dangerous” traffic participants should be higher. As a result, vehicles with a TTC value less than 1.5 seconds (i.e. human reaction time) could be considered as a potential ‘threat’. Therefore, $TTC < 1.5$ is considered to be the context-specific threshold for one motion model. Using this threshold value a position for a vehicle (i.e. *position1*) is calculated by assuming that the vehicle speed is constant for the next 1.5 seconds. Moreover, using the bicycle model’s differential equations another position for the same vehicle is calculated according to its dynamics (i.e. *position2*). Function $\mu_{xy\theta}$ outputs a compromise of the position of the vehicle by calculating the mean value of *position1* and *position2*. Accordingly, other thresholds can be indicated for the rest of the measurements and for other vehicle-level safety contexts.

Summarizing, it can be seen that network-level collision prediction provides an enhancement to vehicle-level risk assessment. Taking into account not only the context of the traffic scene but also the traffic dynamics into account, a faster identification of ‘threats’ can be performed because the probability of a vehicle being dangerous is boosted if the road segment is marked as having collision-prone traffic. Indirectly, the network-level safety hint also affects the identification of kinematic characteristics which may lead to “dangerous” manoeuvres. This is an outcome of the use of context-specific thresholds which estimate vehicle kinematic variables based on the level of safety on both the vehicle and network level.

CONCLUSIONS

The current paper developed a new methodology for the integration of two correlated domains (network-level and vehicle-level) to enhance the risk assessment of AVs. An interaction-aware model based on the Dynamic Bayesian Networks was developed to take into account not only the dependencies of all the vehicles manoeuvres in a traffic scene but also incorporated a hint from network-level collision prediction so as to increase comprehensive reasoning about unsafe behaviour during automated travelling in a road segment. Results from a Random Forest classifier were presented with regards to network-level collision prediction and were used as an example to show the influence of network-level collision prediction on the variables’ probabilities. It is believed that the development of a robust network-level classifier can prove essential to prove if network-level risk estimation can aid the identification of traffic participants which pose a threat to the motion of an autonomous vehicle. However, attention should be given to the correct calibration of the classifier so as to avoid false alarms.

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