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# Global risk assessment in an autonomous driving context: Impact on both the car and the driver

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**Abstract:** Highly automated driving (HAD) is a part of the future ways for the "intelligent" road mobility. In this framework, some studies have shown that drivers' situational awareness decreases when using HAD. In this HAD context, drivers can engage non driving tasks as reading or sleeping. These non-driving tasks lead to increased reaction time in case of hazardous situations or risky events (hardware, sensor, actuator failures, or front obstacle or crashes, or dense traffic congestion, or adverse conditions). In this paper, a global risk indicator is proposed using local information coming from surrounding vehicles or infrastructures (V2X communication). This paper shows firstly the gain of such a global risk indicator comparatively to the local one, and secondly its impact on the behaviour of both the autonomous car and the driver.

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**Keywords:** Autonomous driving; extended perception; global risk; cooperative systems; driver behavior.

## 1. INTRODUCTION

Driving automation has been a subject of research as long as automobiles have existed. It picked up in the 1990s with the ever increasing availability of in-vehicle electronics and sensors. Highly automated driving (HAD) is achieved when the assistance system entirely automates longitudinal and lateral control without the necessity for the driver to monitor the system [1][28][29]. HAD is not yet considered as fully autonomous driving, as it can only function within certain operational parameters, for example in specific road environments. Also, importantly, in HAD the driver will often have to reclaim manual control in critical events; in fully autonomous driving the system is able to take into account hazardous situation and return to low risk conditions on its own.

In [30], the SAE have defined the taxonomy of automated driving levels new widely used by the full community working on this topic. In level 3 and 4 (sharing of the driving task with the driver) HAD systems provide warnings in advance if the driver is required to reclaim control, notably if the system's limits are about to be reached or if some critical event is detected. With some implementations, automation could react to a critical event, but this reaction is usually delayed by asking for the driver to take over [2]. Thus the driver will only react after a delay composed of both the system's delay in assessing the critical event and the time requires for the driver to perceived and understand the situation and to react appropriately. The value of the driver's

reaction time has been shown to be significantly increased by several factors e.g. a lowered vigilance, a lack of situational awareness or an engagement in a secondary task like reading a book, playing videogames, watching a video, etc. [32] propose a study of such a transition stage between the autonomous vehicle and the driver. [34] provides a good review about reaction time in non-critical control transitions. A great part of the collision without ADAS using are mainly due to human perception troubles, interpretation lacks, bad evaluation of the road situations, non-appropriate actions, or non-relevant decisions (figure 2). So, with the sharing of the driving task and with a low level road context attention, the driver will have more difficulties to achieve these human tasks.

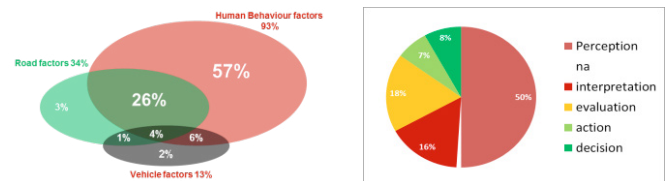


Figure 2: The driver, the weak element in the road context.

In this paper, we test the hypothesis that vehicular communications (V2X) can be used to increase warning time prior critical events requiring driver's action, useful for both the HAD system itself and the driver. Our standard scenario will be a pile-up taking place on motorways lanes. The cause of this crash is not relevant to our research; automation

failure into another vehicle under HAD conditions is one potential such cause (e.g. with platooning).

### 1.1 Rationale

Humans are known to be weak supervisor of automated tasks [4][5]. Previous studies have found that using HAD (and ACC) increases the reaction time in critical events [6]. However, it has also been shown that a timely warning was enough to avoid most collisions [6].

HAD drivers were found to take 2.5 seconds longer than manual drivers to react to a traffic light change or approaching vehicles [7]. Several studies have focused on hard braking front vehicle scenarios, where HAD were always found to react slower than manual drivers: from 28% [8], and 42% [3], to 88% [9] slower. Such lower reaction times can be explained by the ease of engaging in activities unrelated to driving [10] or drowsiness arising from monotony [6]; passiveness is highly likely to arise under HAD conditions [11]. Compounding to the increased likelihood of distractions by non-driving related activities, HAD drivers often find themselves driving with shorter headways than other drivers. For example, at the onset of traffic jam [12] found that HAD drivers had an average headway of 2.2 seconds, to compare with 3 and 2.8 seconds for manual and ACC drivers respectively.

However, studies which are yet to be completed, and call for caution have also suggested that a proper warning could allow most drivers to react timely to critical event [6]. For example Gold et al. [13] have shown that 7 seconds of advanced warning of a control transition could be sufficient for HAD drivers to safely resume control and to avoid a stationary object in front of their vehicle. [34] reported a higher required time of 15 seconds for early recovery or 40 seconds for the stabilization of the vehicle in the study of the latter authors, whether the recovery is anticipated or due to a critical event. Some recent studies show that the reaction time can be reduced to a certain extent by implementing drivers training [36]. The reaction time issue may be enhanced also by the provision of an adapted assistance to the drivers, for example by directing the driver's attention to the source of danger for a minimum of 6 seconds before the situation becomes dangerous [37].

In this paper, we aim to demonstrate that V2X technology can deliver the performance to provide an advance warning for HAD drivers, and generally outperform a system based solely on local information. The advantage of using V2X over in-vehicle sensors only is evident when considering a string of vehicles on the motorway: the immediate downstream vehicle will obstruct the view of vehicles further downstream. If an emergency incident (sudden braking, loss of control, etc.) takes places a few hundred metres away from the ego-vehicle, neither its driver nor any sensor will have a way to know about that event. With the reaction time of each subsequent vehicle adding, it is unlikely that any drivers would have enough time to react, especially with any degree of automation and its corollary of increased reaction time and reduced headways. On the other hand, V2X will allow

propagating information about the incident to the rest of the string very quickly.

We have previously studied the performance of a simple warning dissemination system on tracks [14] and collected extensive data on V2X performance [15]. In this paper, we will show that an augmented perception system combining local sensor and V2X can indeed provide additional warning to HAD drivers in emergency situations.

## 2. METHODOLOGY AND SYSTEM ARCHITECTURE

This study focused on simulation. We designed a simulated augmented perception system that collect information from local (ego-vehicle's sensors) and remote (other vehicles) sources and fuse them into a single "augmented map"; any relevant information can be stored in this map. The simulation is supported by our V2X performance model built from empirical data [16]. A test scenario is then replayed several times, to allow variations of headway; the scenario involves a vehicle performing a sudden heavy braking in a motorway context.

Our approach uses two levels of simulation abstraction. At first, microscopic simulation related to individual vehicle. The simulator we are using is the SiVIC-RTMaps™ framework as described in [18]. SiVIC was designed to support a limited number of vehicles (typically less than 10) and cannot simulate large traffic. The second level of abstraction allows us to simulate interaction between large numbers of vehicles; it is a microscopic traffic simulation, linked to a wireless network simulator. We used the VEINS [19] framework that combines the open-source SUMO traffic simulator with the OMNet++ network simulator. The two approaches are complementary, as they allow testing the same scenario both at the individual and collective level. The methodological adjustments required by these two different levels are described where appropriate.

In the following sub-sections we will present in further details each part of the simulated augmented perception architecture.

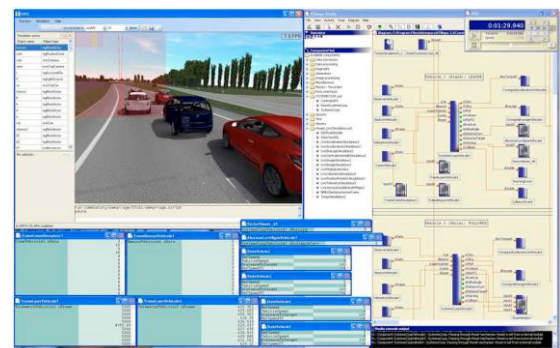


Figure 3: The SiVIC-RTMaps™ screens, showing the SiVIC visualisation on the left and the top-level component architecture in RTMaps on the right; various data vectors are shown at the bottom left.

### 2.1 Software components

The two softwares used are SiVIC-RTMaps™ and VEINS. We developed our C-ITS simulation framework in SiVIC-RTMaps™ as presented in [18, 20] (figure 3). SiVIC allows to model and to simulate the vehicles, infrastructure, embedded sensors, and the communication means. RTMaps is the prototyping platform allowing implementing the cooperative ADAS application. A scenario-specific module is added in the simulation framework, which was also adapted inside VEINS so the communications and control algorithms would function similarly.

## 2.2 Local perception

At the base of the augmented perception system is the local perception. All vehicles are equipped with a number of sensors, both proprio- and exteroceptive.

GPS and any combination of inertial sensors can be used for localization, while the vehicle perceives its environment via radars or laser scanners. In the present study, we have a GPS and a forward-facing ranging sensor (LIDAR) on all vehicles. The ego-vehicles and other objects build from sensors are stored in a standardized state-vector, updated every 50 milliseconds. The state-vector contains: (1) a unique object ID, (2) timestamps, including  $T$  the most recent timestamp in the common temporal reference, (3) the position in two coordinates systems (WGS84 and Lambert conformal conics), (4) a speed vector, (5) the object variance-covariance matrix, (6) a confidence value in the object's existence (expressing the quality of data), (7) the object's first detection timestamp, and several flags used in the map building process.

## 2.3 V2X communication

The V2X simulation differs in each software architecture. In SiVIC-RTMaps™ a custom built transponder system [20] is paired with our performance model [16]. In VEINS the complete WAVE stack is simulated; the performance model by Sommer *et al.* [23] is used, which is also based upon empirical data collection, and yields performance very similar to ours. The main difference between the two models is the type of simulation they were designed for: the model from Sommer *et al.* is designed for telecommunication studies, while our model was designed to support cooperative application research with a computationally inexpensive model. Each vehicle broadcast its own state-vector and the state-vector of any object is has detected using local sensors; the broadcast frequency is 2 Hz.

## 2.4 Extended and augmented perception

The augmented perception architecture's process is broken down into three stages: (1) spatial and temporal synchronization, (2) association and tracking, and (3) fusion. The architecture is designed for a decentralized map-building approach, i.e. one where each vehicle computes its own augmented map. State-vectors coming from the ego-vehicle's local perception system and received via V2X from other

vehicles are synchronized spatially and temporally via the prediction step of a linear Kalman filter. The object's behavior is evaluated to a common timestamp considered the "present" time. The association and tracking uses the robust Multi-Hypothesis Tracking (MHT) algorithms proposed in [25] to associate previously known objects with new data. Finally, the fusion stage fuses those new and older objects through the update stage of a linear Kalman filter. The augmented map is functionally similar to the local maps, but contains more accurate objects as they have been updated with information from more data sources. The flow of data is strictly controlled to avoid any data independence issue (for example, the augmented state-vectors are never broadcasted).

## 2.5 Global risk assessment

To provide early warning about critical emergency events, the system needs to know how risky the current driven context is. This is achieved via the "augmented risk"  $R_{aug}$ , an instantaneous crash risk metric, computed from an individual risk. [40] shows that the Time To Collision (TTC) and the Time Headway (TH) are, combined, a good approximation of the risk in case of a deceleration. One criteria by itself cannot manage specific situations: if vehicles drive close to each other as the same average speed the situation can be described as more risked than if they drive at larger distances and TTC is not consistent with the risk. In previous work, we integrate both measure to represent the probability of collision.

Here, the individual risk metric is evaluated depending on the current situation and expected actions from vehicles in the environment [26]; as a risk, it relies on two components. First, the collision probability is evaluated using a Monte-Carlo test on several parameters (driver reaction time, driver's actions, etc.) of a subject vehicle given its environment. Next, the severity of the collision, if it were to occur, is computed as a rear-end crash using the speed difference at the moment of collision (using the Maximum Abbreviated Injury Scale based on the EES – Equivalent Energy Speed). The augmented risk is then constructed in a three steps process. Let us have a string of  $n$  vehicles:  $\{v_1, \dots, v_n\}$ . For a pair of vehicles  $i$  and  $j$ , there is  $R_{j,i}$  that expresses the risk of collision between those two vehicles, as measured by vehicle  $i$ .  $R_{j,i} \in [0, 1]$ . If the risk equals 1, the crash is inevitable or has already happened. Depending on the information available to each individual vehicle, we may have  $R_{i,j} \neq R_{j,i}$ .

A vehicle equipped with multiple sensors or V2X communications have an array of risks associated with each vehicles it can detect:  $\{R_{1,i}, \dots, R_{n,i}\}$ . From there, we can create a global risk value  $R_{g,i}$ , which is defined as the global collision risk as perceived by vehicle  $i$ . This value becomes relevant when a vehicle has access to multiple sources of information. Importantly, another vehicle nearby might not have access to the same information; thus, the value of  $R_{g,i}$  for each vehicle will change depending on their awareness of the overall driving context. Eq. 1 shows how we compute  $R_{g,i}$ .

$$R_{g,i} = \max(R_{1,i}, \dots, R_{n,i}) \quad (1)$$

If all vehicles share their individually perceived risk of the driving situation we can then create an augmented collision risk called  $R_{aug}$  (Eq. 2).  $R_{aug}$  is the combined risk for the whole driving context.  $R_{aug}$  is most informative if its scope is limited; indeed, if there is a single dangerous event in a string of 1,000 vehicles,  $R_{aug}$  will only return a very small increase in the total risk.

$$R_{aug} = \frac{1}{n} \sum_{j=1}^n R_{g,j} \quad (2)$$

$R_{aug}$  is a risk estimation (gathered from communicating vehicles) which will be greater than the local risk  $R_{g,i}$  if a crash occurs among communicating vehicles. The knowledge of the overall risk  $R_{aug}$  will give extra time to a system or drivers to react (for example by disabling HAD). Our approach is similar but simpler than the average-based risk valued computed in [27], as we do not weigh the risk values received from other vehicles.

We select a 0.7 value for  $R_{aug}$  as dangerous threshold, which corresponds to high crash probabilities (especially with multiple vehicles involved) and higher severity ranges. This threshold is also high enough to avoid a single vehicle from pushing the risk too high when the overall driving context is not that risky.

However, because of methodological limitations in the VEINS-based simulation, this threshold cannot be used as it. Indeed, VEINS cannot simulate crashes, only near-misses (very short headways). As such, it is impossible for the risk to reach 1 (although we can artificially enforce it in post-processing by forcing the risk value). This lead us to use, for that specific simulation, a smaller threshold of 0.4.

### 3. RESULTS

The SiVIC simulation takes place on a reproduction of the Satory (France) test tracks, representing a motorway's single carriageway. The location of the braking event is predetermined, as well as the string's composition, although the headways are random. Five vehicles are involved in the scenario, with the leading one performing the emergency braking. The control algorithms [18] attempt to maintain a 2.5 seconds headway, and react to changes with a human-like reaction time of 0.5 second. Each vehicle assesses its  $R_{g,i}$  value from data available locally. Since they only have a forward-facing LIDAR,  $R_{g,i}$  is equal to  $R_{i-1,i}$ , the risk for the vehicle driving in front. For the analysis we focus on the last vehicles ( $i=5$ ). Figure 4 shows the results of two simulation runs, while more results are collated in Table 1. The principal analysis metric is  $dt_5$ , the different between  $t_{L,5}$ , the time at which the local perception returns a risk greater than the danger threshold, and  $t_A$ , the time at which the augmented perception does so;  $t_A$  and  $t_{L,5}$  count the seconds after the critical event. All the  $R_{g,i}$  are presented on the figure, as well as  $R_{4,5}$  (plain dashed black line) and  $R_{aug}$  (plain red line). In the scenario, the automated controller does not have enough time to react and crash, hence the risk value are all jumping

to 1. As shown in Table 1,  $dt_5$  is at least 6 seconds. The warning time provided by a local-only system is at most 5 seconds in the very best case scenario, but often less as seen with the fifth vehicle (2 to 3 seconds). Note that this is counted before the collision between vehicles  $i$  and  $i-1$  as vehicle  $i$  has no way of knowing what is going on further than vehicle  $i-1$ . The consistent 6-7 seconds  $dt_5$  values show that the augmented perception system is capable to deliver the necessary warning (up to 13 seconds before a potential collision) for a driver to retake control from HAD mode if a critical event is undergoing a few vehicles downstream. The average time for the whole platoon to become aware of the danger is  $\bar{t}_A = 3,56$  seconds. The limitation of this result is that vehicles driving closer to the critical event will not benefit much from the augmented perception system. The VEINS simulation takes place on an accurate reproduction of the Pacific Motorway segment stretching 45 km away from Brisbane's CBD. The exact location of the braking event and the composition of the string at that point are random; the traffic density is 2,500 vehicles/hour. The aim of this scenario is to confirm results obtained in the previous subsection with a different approach.

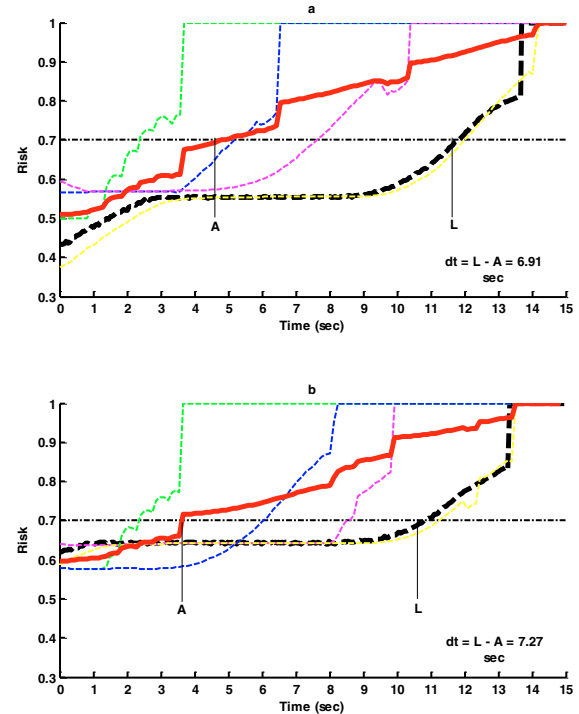


Figure 4: Two runs of the SiVIC simulation showing the  $R_{g,i}$  for vehicles 2 (green), 3 (blue), 4 (magenta), and 5 (yellow), as well as  $R_{4,5}$  (dashed black) and  $R_{aug}$  (plain red). A and L are  $t_A$  and  $t_{L,5}$  respectively;  $t = 0$  is the beginning of the emergency braking.

Figure 4 shows an example of a run; the X-axis shows the time after the critical event. The red line is  $R_{aug}$ , the other lines are the various  $R_{g,i}$  (local risks in each vehicles), note that they decrease after some time because the SUMO car-following model will not allow for a collision; each subfigure present the augmented risk obtained with an increasing



number of vehicles accounted for. It demonstrates well the issue of choosing an appropriate radius for the evaluation of  $R_{aug}$ : if too many vehicles are included in the count, because they are too far away from the critical event they lead to underestimation. The middle subfigure corresponds to the same case as the SiVIC simulation.

$t_A$	$t_{L,S}$	$dt_S$
4.65	11.56	6.91
3.28	10.55	7.27
3.52	9.86	6.34
3.6	10.83	7.23
3.16	10.43	7.27
3.2	10.81	7.61

Table 1: Variations of  $dt$  over 6 simulation runs, representing the extra warning time available to the fifth vehicle in the string.

The VEINS results present a similar pattern as to the SiVIC ones: the augmented risk can be used to improve the warning time provided by a local perception system. Specific numerical results are given in Table 2. The fifth vehicle is warned about 10 seconds after the event by local perception (like in the previous simulation) and gets about 3 seconds of additional warning if  $R_{aug}$  is computed with 4 vehicles. Forcing a crash (having  $R_{g,2}$  set to 1) yields similar results (see last row of Table 2). The different methodology, and particularly the lack of extreme maneuvers in VEINS that can indeed take place in SiVIC, explain this difference.

#### 4. IMPACTS ON VEHICLES AND DRIVERS

In this paper, we only focus on the driver's reaction time as the driving behaviour parameters to investigate the impact of V2X on safety. One of our perspective is to integrate the safety impact of the trajectory decision taken by the drivers in the critical situation. Indeed, depending on the road scene configuration and the drivers' level of awareness of the situation, they can decide to turn the wheel on the right or on the left (e.g. to avoid the vehicle ahead), or they can keep the trajectory. A supplementary dimension in terms of safety impact evaluation lies in the evaluation of consequences of the drivers' actions and decisions on the environment and the other road users (e.g. drivers of manual cars, Automated Vehicles in automated mode, drivers of 2-wheelers, etc.).

By the way, several human-related impacts of driving automation have been documented in the literature in terms of impact on performance and security. Drivers may become overconfident in automation and tend to disengage in the task. They can experience mental overload or under-load. They can have a weakened understanding of the operation and status of the automatic system, as well of the driving situations. In the medium and long time, they also could lose the skills required to drive and operate the car in security. Some authors have also described a shift towards more risky behaviors by drivers using driving automated assistance. For example, [38] showed that cruise control users react later and reduce safety margins. More recently, [39] observed that users of an Autonomous Emergency Brake system coupled

with an alarm were more likely to let the system react in the case of critical event whereas a higher number of drivers intervene before the automatism in the absence of the advance warning. While all these risk factors have an effect on drivers' time needed to react appropriately, they have different implications in terms of required assistance and risk prevention measures to support resuming control. The use of specifically dedicated scenario using the SiVIC framework could provide an interesting means for evaluating their impact on safety at a more "systemic" level.

#### 5. CONCLUSION AND FUTURE WORKS

In this paper, we have tested the hypothesis that V2X technology can provide an early warning to vehicles operating under HAD mode, so that their drivers can safely reclaim control in case of a critical event. Our main metric uses the concept of "augmented risk" calculated from information collected by local sensors and transmitted over V2X networks. Using two different simulation environments we have found that V2X outperform a local perception system (such as ACC) for most vehicles in a 5-6 vehicles string. Local perception systems rarely provided more than 3 seconds of warning before the ego-vehicle was to crash into the downstream vehicle. Previous research have shown that 3 seconds is not enough for HAD drivers to reclaim control. On the other hand, V2X allowed adding 6-7 seconds to the time provided by local perception. With V2X, the whole group could be warned of the critical event about 3.56 seconds after the beginning of the event, providing increasingly large pre-warning for upstream vehicles. Our result also shown that the number of vehicles accounted for in the calculation of the augmented risk is a very important factor in providing a timely warning.

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