ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/335729829

Risk Management for Intelligent Vehicles based on Interval Analysis of TTC

Article · January 2019

DOI: 10.1016/j.ifacol.2019.08.110

CITATIONS
0

READS
55

4 authors:

Nadhir Mansour Ben Lakhal
Université Clermont Auvergne
6 PUBLICATIONS **11** CITATIONS

SEE PROFILE

Lounis Adouane
Université de Technologie de Compiègne
110 PUBLICATIONS **582** CITATIONS

SEE PROFILE

Nasri Othman
Ecole Nationale d'Ingénieurs de Souss
30 PUBLICATIONS **106** CITATIONS

SEE PROFILE

J. Ben Hadj Slama
University of Sousse
116 PUBLICATIONS **585** CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project Nonlinear Progressive Accommodation View project

Project Design and control of collaborative, cross and carry mobile robots : C3Bots View project

All content following this page was uploaded by Nadhir Mansour Ben Lakhal on 13 September 2019.

The user has requested enhancement of the downloaded file.

Risk Management for Intelligent Vehicles based on Interval Analysis of TTC

Nadhir Mansour Ben Lakhal [*,**] **Lounis Adouane** [*]
Othman Nasri [**] **Jaleleddine Ben Hadj Slama** [**]

[*] *Institut Pascal, UCA/SIGMA - UMR CNRS 6602, Clermont Auvergne University, France*
[**] *LATIS Lab, National Engineering School of Sousse (ENISo), University of Sousse, BP 264 Sousse Erriadh 1023, Tunisia*

Abstract: Several risk management strategies are integrated into today's intelligent vehicles to guarantee safety. To be efficient, these strategies must handle the uncertainty propagation into the navigation process. For a more reliable risk management, this work presents a novel set-membership over-approximation of the Time-To-Collision (TTC), which fits a vehicle following scenario. The interval analysis is used to consider different uncertainty sources with respects to surrounding measurement conditions. For optimization aims, statistical properties of the measurements, which are based on the correlation evolution, are employed to avoid conservative results. It is assumed that the vehicle dynamics and correspondingly the correlation between measurements cannot drastically change in a short time horizon. Accordingly, the amount of uncertainty assigned to each measurement, evaluated per interval, is decreased. This fact prohibits irregularities in the correlation relating variables. The proposed risk management approach is integrated into the architecture of an Adaptive Cruise Control (ACC). Simulation results prove the overall risk management efficiency and its ability to handle uncertainties.

Keywords: Intelligent transportation systems, risk management, time to collision, interval analysis, correlation, uncertainty, adaptive cruise control.

1. INTRODUCTION

Over the last decade, the need to improve mobility has entailed a great evolution in Intelligent Transportation Systems (ITS). Accordingly, modern cars have been equipped with various collision avoidance systems. Due to the critical operational context of such mechanisms, ensuring the road safety has become as a major concern for the ITS community. Based on Naufal et al. (2018), it is mandatory to involve hazards into the decision-making level of the collision avoidance systems. For this purpose, numerous probabilistic methods have been practiced to achieve threats analysis. As shown in Noh and An (2018), it is frequent to use the Bayesian Networks as a risk-sensitive decisional strategy. Iberraken et al. (2018) have proposed a multi-level Bayesian Decision Network to handle lane change maneuvers. The latter is utilized for situation assessment in highways and safety verification of the performed maneuver. Under different urban traffic situations, Funfgeld et al. (2017) have developed Monte Carlo simulations to select a safe maneuver. To carry a crash-free lane change, fault tree analysis has been adopted by Park et al. (2018).

A considerable limitation of these techniques is being sensitive to the modeling and the evaluation of the uncertainties. Generally, hazard analyses are built based on probabilistic prediction. This forecasting relies on assessing the chance of an event manifestation, which may mismatch the reality. Correspondingly, the prediction step is usually enhanced by using safety indicators. Through real measurements, these indictors make the forecasting closer to reality to succeed the hazard prediction. Systematically, the risk assessment efficiency depends on the safety indicator accuracy. In particular, the Time To Collision (TTC) estimation as a hazard indicator is the most widespread, see Chen et al. (2018) and Iberraken et al. (2018).

The TTC calculation has been carried out in a stochastic manner. It has been conjoined with a model-based prediction of the vehicle future trajectories. The crash occurrence probability was calculated according to this model findings, see Tan and Huang (2006). The main drawback presented by this stochastic TTC is being estimated through uncertain vehicle dynamics. For the sake of accuracy, more interest has been focalized on deterministic rules. Vehicle speeds have been assumed to be constant during a short time horizon. In that way, the TTC is roughly defined as the ratio between the distance separating two vehicles and their relative velocity. Currently, great efforts are being made to reach an accurate formalization of the TTC. For more details, readers are referred to Hou et al. (2014). Practical solutions to make ITS risk management approaches more accurate are highly needed. To handle this issue, the majority of researches attempt to ameliorate risk indicators precision by decreasing uncertainty in measurements. Several stochastic/statistical approaches have been practiced for this aim. However, these methods have poor performances when the studied system is unwell conditioned. As an example, for Kalman filters, a very careful characterization of uncertainties and accurate knowledge for the system initial state are required, see Nicola and Jaulin (2018). In the opposite case, good measurements may be rejected and considered as outliers. After all, these stochastic/statistical methods are sensitive to non-linearity, see Wang et al. (2018). Moreover, the measurement noise is assumed to be of a particular probability distribution e.g., Gaussian distribution. This assumption does not always hold.

In this paper, a novel set-membership extension for the TTC is proposed. To the best of the author's knowledge, this is the first TTC extension, which handles interval data. Its key contribution lies in incorporating the uncertainty propagation into the collision prediction. It assures a TTC approximation strongly robust to measurement uncertainty and communication latencies. Furthermore, the proposed approach includes a statistical optimization step. The evolution of the correlation between measurements has been monitored. This characterization of correlation serves to narrow interval-measurements, which are used for the TTC approximation. Together, the set-membership approach and the correlation characterization compromise between safety and optimality to present a guaranteed assessment of the TTC. The suggested risk management approach has been tested on an Adaptive Cruise Control (ACC) system, see Dahmane et al. (2018).

The remaining of this paper is organized as follows: Section 2 explains the adopted uncertainty assessment strategy for the navigation process. Section 3 details the optimization step in the uncertainty estimation and introduces the novel set-membership TTC computation algorithm. Section 4 describes the integration of the proposed risk management approach into an ACC architecture. Section 5 illustrates the realized simulation work and interpret the obtained results. Section 6 summarizes this paper main contributions and discusses future work.

2. SET-MEMBERSHIP TTC FORMALIZATION AND UNCERTAINTY QUANTIFICATION STRATEGY

For a car following scenario, a precise TTC formalization is given by the standard equation of motion, describing the displacements between the follower and leader. In our case of study, the navigation dynamics are provided by sensor measurements and inter-vehicular communication. Consider two vehicles i and j with vector positions and velocities of: p_i, p_j, V_i and V_j. Here, i and j are respectively the in-front vehicle "leader" and the ACC-equipped vehicle "follower" (cf. Figure 2). Henceforth, the follower velocity V_j is considered exact and non uncertainty is associated to this variable. The ACC is assumed to acquire the V_i with a Vehicle-to-Vehicle (V2V) data exchange. Hence, Ward et al. (2015) have proved that the rate of change in the separation between i and j, denoted $\dot{d}_{ij}$, is expressed as:

$$\dot{d}_{ij} = \frac{1}{d_{ij}}(p_i - p_j)^T(V_i - V_j) \tag{1}$$

Where d_{ij} is the measured inter-distance separating i and j. Thus, Ward et al. (2015) have derived the TTC value from equation (1):

$$TTC = -\frac{d_{ij}}{\dot{d}_{ij}} \tag{2}$$

Obviously, the above generalized approach of TTC estimation does not consider the uncertainty impact on the observations. This paper main contribution is introducing a novel set-membership TTC extension. It takes into account latencies and the uncertainty propagation into the navigation process. Usually, complex stochastic techniques are developed to estimate the uncertainty propagation in a given process. However, these methods reliability stills for yet a vast controversial issue due to their probabilistic nature, see Nicola and Jaulin (2018). As an alternative, interval analysis is used in this work, see Jaulin et al. (2001). The information inaccuracy is handled thanks to a prior knowledge of the uncertainty amounts affecting data. Accordingly, the natural representation of data is extended to intervals. The mathematical operations $(+, -, *, /)$ are also extended to intervals to assess the uncertainty evolution all along any algorithm. The set-membership computation is assumed as guaranteed and reliable since the exact value of data is enclosed inside an interval bounds. In what follows, $[x] = [\underline{x}, \overline{x}]$ denotes a real interval, where $\underline{x}$ and $\overline{x}$ are respectively its lower and upper bounds. The width associated to $[x]$ underlines the uncertainty extent.

To extend the TTC approximation to intervals, it is mandatory in a first step to construct a relevant strategy to define measurement bounds. A cause-effect relationship between uncertainty sources and interval widths must be established. In the sequel, the uncertainty is properly evaluated referring to the following categories:

a) Factors related to the communication and the surrounding environment: Multiple conditions emphasize the uncertainty impact on the performances of the vehicle's sensing tools. Nowadays, the vehicular connectivity enhances the in-road safety through wireless communication as the Dedicated Short Range Communication (DSRC). For this reason, a great focus is given in this section to analyse the DSRC latency. In particular, a recent research, conducted by Dey et al. (2016), has investigated this issue through in-field tests. It has been proven that the V2V message delivery time increases relatively to the vehicle speed. Otherwise, the communication latency is related to the number of vehicles present in the car nearby. Since more vehicles transmit messages, communication conflicts invoke extra-latency. Correspondingly, Tables 1 and 2 illustrate the experimentally derived upper and lower limits of the DSRC latency, see Dey et al. (2016). The uncertainty amounts affecting the V2V communication-issued data are recognized based on these results.

Table 1. DSRC latency at different speeds

Vehicle speed (m/s)	Minimum latency (ms)	Maximum latency (ms)
9	89.35	89.39
15	93.35	93.84
22	96.10	96.16
31	101.47	101.54

Table 2. DSRC latency at different number of vicinity vehicles

Neighborhood vehicles number	Minimum latency (ms)	Maximum latency (ms)
10	35.47	35.54
20	50.66	50.70
30	66.63	66.66

From now, $[T_{V2V}]$ designates the interval characterizing the aforementioned V2V latencies. Hence, the positioning tools accuracy depends on the satellites masking and signals attenuation. In this work, it is supposed that a signal strength indicator associated to the navigation road section is available. The uncertainty impacting the positioning are fixed relatively to this indicator. Besides, the measurement of vehicles inter-distance is prone to important uncertainty. To cover the measurement imperfections, a 1% of uncertainty is admitted on the inter-distance. Finally, all the exchanged data through V2V communication, such as V_i, are assumed erroneous with a range of 0.5% due to the leader measurement imprecision.

b) Vehicle internal factors: Uncertainties may result from the intra-vehicle latencies, which slowdown the vehicle response to threats. Foremost, it includes: sensors update time and the required time for data propagation through the automotive embedded system. These parameters are fixed by the designer depending on the concerned vehicle characteristics. Before proceeding further, let denote $[T_L]$ as a predefined interval associated to such latencies.

Obviously, it is judicious to subtract $[T_{V2V}]$ and $[T_L]$ from the TTC value since these latencies may increase in unpredicted way a given situation criticality. Under this assumption, equation (3) introduces the TTC set-membership final shape:

$$[TTC] = -\frac{[d_{ij}]}{[\dot{d}_{ij}]} - [T_{V2V}] - [T_L] \tag{3}$$

The above formalization takes precautions against all potential uncertainties. The TTC approximation is correlated with the risk influencing factors and parameters that govern the uncertainty evolution. Furthermore, it is robust to vehicular communication latencies.

3. CORRELATION-BASED OPTIMIZATION STEP

The previous section has detailed how to appropriately pick-up a TTC over-approximation. Clearly, admitting the worst-case of risk and a maximum level of uncertainty, is the safest decision. However, a too conservative risk-management degrades the navigation performances. The worst case of risk manifestation definitely mismatches the reality. To overstep this limitation, an optimization step is joined to the initially suggested TTC over-approximation. It exploits the historical characterization of the data structure to ensure more optimistic results of TTC. To reach this goal, our approach relies on the real-time monitoring of the correlation. The concept of the correlation has been widely employed for reliability models and diagnosis. The real-time monitoring of the correlation and the characterization of system variable's dependencies are highly efficient in this context. A system correct behavior is proven by a smooth transition in the correlation states, see Xia et al. (2017). Especially in a short sampling-time step, the correlation changes suddenly in a drastic way only in presence of anomalies. Anomalies include faulty or aberrant measurements, modification in noises statistical features, deep change in the control process, etc. This is the case for the navigation process studied in this paper. A sudden change in the vehicle dynamics or in the environmental conditions is generally unrealistic in a very short time horizon. Correspondingly, the real-time supervision of the correlation is adopted in this work. It prohibits modification in the correlation real structure due to the uncertainty attributed to each interval of measurements. Interval widths are reduced progressively to guarantee a minor fluctuation on the correlation between successive instants t_{k-1} and t_k. In this regard, a more realistic prediction of the uncertainty evolution is reached while balancing between utility and safety.

Mainly, the correlation has been developed to perform dependency analysis of single-valued variables:

$$C_{X,Y|k} = \frac{COV_{X,Y|k}}{\sigma_X \sigma_Y} \tag{4}$$

Note that $C_{X,Y|k}$ is the correlation factor between two variables X and Y at instant t_k. $COV_{X,Y|k}$ is the covariance associated to X and Y. σ_X and σ_Y are respectively their variances. In this paper, the vertices transformation is utilized as symbolic manner to represent interval data. In previous work, we have used this transformation to extend a diagnosis approach to intervals, see Lakhel et al. (2016) and Gueddi et al. (2017). However, this method has not been yet applied to study the uncertainty propagation into a risk management process. Consider an interval data matrix X^I, which is built by N observations describing m interval-valued variables $[x_{i|i=1..m}]$:

$$X^I = \begin{pmatrix} \left[\underline{x_1(1)}, \overline{x_1(1)}\right] & \cdots & \left[\underline{x_m(1)}, \overline{x_m(1)}\right] \\ \vdots & \ddots & \vdots \\ \left[\underline{x_1(N)}, \overline{x_1(N)}\right] & \cdots & \left[\underline{x_m(N)}, \overline{x_m(N)}\right] \end{pmatrix} \tag{5}$$

The vertices method provides an equivalent single-valued matrix for X^I with the same data structure. All the vertices (min/max bounds of intervals) are implied to define a new single-valued matrix, denoted X^H. Geometrically, all m intervals and N observations represent a hyper-rectangle of 2^m vertices. Thus, X^H is constructed from $N \times 2^m$ rows and m columns:

$$X^H = \begin{pmatrix} \begin{pmatrix} \underline{x_1(1)} & \cdots & \underline{x_m(1)} \\ \vdots & \ddots & \vdots \\ \overline{x_1(1)} & \cdots & \overline{x_m(1)} \end{pmatrix} \\ \vdots \\ \begin{pmatrix} \underline{x_1(N)} & \cdots & \underline{x_m(N)} \\ \vdots & \ddots & \vdots \\ \overline{x_1(N)} & \cdots & \overline{x_m(N)} \end{pmatrix} \end{pmatrix} \tag{6}$$

Consider X and Y two variables that represent each time two distinct columns from the X^H. In such a manner, $COV_{X,Y|k}$ is computed by the mean of several sample measurements of X and Y. The vertices transformations depends exponentially on the variables number m and linearly on the observations number N. In this work, the correlation is assessed separately between two variables, which means $m = 2$. Thus, the vertices transformation, in our case of study, does not imply any computational complications. Figure 1 illustrates the application of this technique in this work.

Once the equivalent single-valued data are obtained, it is possible to proceed the correlation assessment. The uncertainty minimization is done at each sampling step for each

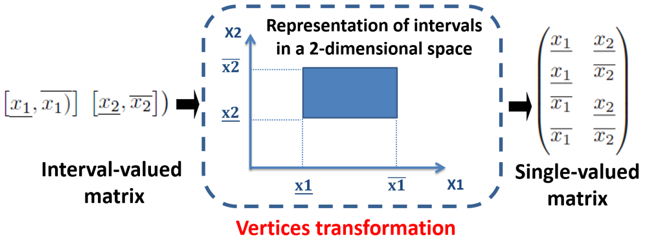

Fig. 1. Vertices technique applied to estimate correlation

couple of variables intervening in the TTC calculation. With each newly incoming set of interval observations, the correlation assessment is done with previous measurements samples. The interval, having the largest width, is targeted by the minimization. After that, the vertices transformations is applied and the gap in the correlation between instants t_k and t_{k-1} is obtained. The uncertainty reduction is aborted at two conditions:

Condition 1: When the gap in the correlation between two instants t_{k-1} and t_k decreases from an iteration to another and suddenly it begins to increase. This fact means that the concerned interval was tightened as much as possible. More reduction in the interval width will entail undesired modification in the data proper distribution.

Condition 2: When the gap in the correlation between two instants t_{k-1} and t_k exceeds the minimum variation of correlation noticed in the system nominal behavior. This latter is characterized through off-line simulations.

Finally, algorithm 1 summarizes the optimized TTC over-approximation process.

Algorithm 1: TTC optimized over-approximation

Input : p_i, p_j, V_i, V_j, $d_{i,j}$ and $[T_L]$.
Output: $[TTC]$.

while *Navigation process is running* **do**
  -Estimate $[T_{V2V}]$, $[d_{i,j}]$, $[V_i]$, $[p_i]$ *and* $[p_j]$ *according to the measurement conditions (cf. Section 2).*
  for *each couple of variables between* t_{k-1} *and* t_k **do**
    repeat
      -Apply the vertices technique (cf. Section 3).
      -Calculate the correlation factor at instant t_k *(see equation (4)).*
      -Estimate the gap in the correlation between instants t_k *and* t_{k-1}*:*
      $C_{X,Y|k} - C_{X,Y|k-1}$
    until *Condition 1 or Condition 2 is satisfied*
  end
  -Calculate the $[TTC]$ *(see equation (3))*
end

4. SET-MEMBERSHIP RISK MANAGEMENT INTEGRATION INTO AN ACC ARCHITECTURE

The current section describes the integration of the suggested TTC approximation method into the risk management layout of an ACC. Basically, the studied ACC operation is arranged by switching between two modes:

Cruise Control (CC) Mode: If the closest car to the host vehicle is too far, the ACC system triggers a dynamic target reaching. This target is pointed out according to a user predefined speed.

Adaptive Cruise Control Mode: The presence of vehicles in the host car vicinity activates the ACC mode. It maintains a reference distance, denoted d_{ref}, from the vehicle ahead. Indeed, a safe target enclosure is derived after appropriately calculating $[d_{ref}]$ with interval arithmetic. $[d_{ref}]$ represents the distance between the zero distance (from the leader position) and the value varying between $\underline{d_{ref}}$ and $\overline{d_{ref}}$. Figure 2 illustrates the proposed ACC.

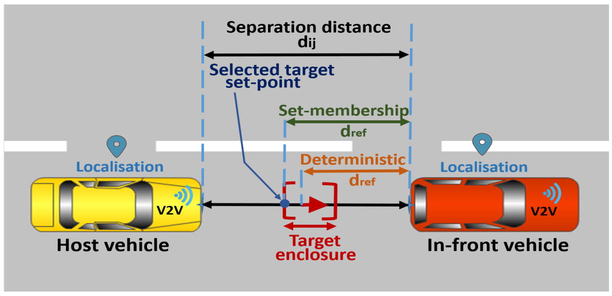

Fig. 2. Proposed ACC system principle

To ensure the aforementioned modes, a particular multi-controller architecture (see Adouane (2016)), which is enhanced by a risk management module, is designed. As shown in Figure 2, the ACC acquires the required information by the V2V communication and the localization tools. At this moment, the "uncertainty assessment block" checks the measurement conditions and transforms all the data to intervals. Once interval measurements are obtained, the correlation supervision step begins. The initial interval measurements are tightened to permit a more compact [TTC] estimation. Depending on the obtained results, the suitable mode is selected. If the ACC mode is activated, the "target selection block" makes an optimal and safe choice of the target set-point. By admitting the upper bound of the reference distance $\overline{d_{ref}}$, the selected target ensures a greater TTC and more of safety. Let denote by $[\tilde{T}]$ the time to travel $[d_{ref}]$. A key component parameter, which should be considered to define $[\tilde{T}]$ and respectively $[d_{ref}]$ is the host vehicle time-to-stop. Under critical circumstance as a follower hard breaking, the ACC-equipped vehicle requires a short period of time $[T_{bre}]$ to accomplish a full breaking. $[T_{bre}]$ is computed by equation (7), where a is the vehicle deceleration rate. For simplicity, a is assumed to be a constant interval.

$$[T_{bre}] = V_j/[a] \tag{7}$$

Hence, $[\tilde{T}]$ and $[d_{ref}]$ must satisfy the following relations:

$$[\tilde{T}] = [T_{bre}] + [T_{min}] \tag{8}$$

$$[d_{ref}] = [\tilde{T}] \times ([Vi] - Vj) \tag{9}$$

Note that $[T_{min}]$ is a predefined minimum safety temporal distance. Accordingly, the follower navigation is assumed to be safe under the condition that $\overline{d_{ref}}$ is utilized to define the target set-point. It should be noted that the target selection strategy is neither too conservative, nor optimistic thanks to the correlation supervision step. Finally, a control unit allows reaching the selected target with a desired velocity. More details about the adopted ACC architecture are illustrated in Figure 3.

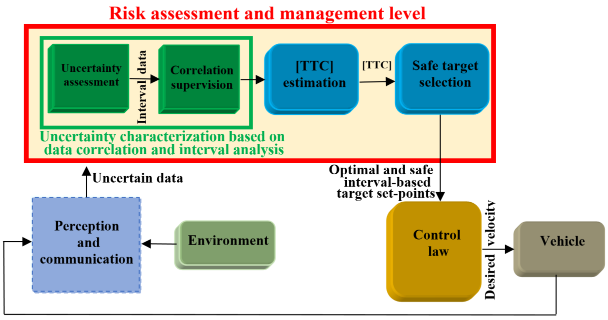

Fig. 3. Control architecture of interval analysis-based ACC

5. SIMULATION SETUPS AND RESULTS

To validate the proposed risk-management schema, simulation results are presented in this section. Test scenarios have been developed on a Matlab 2D autonomous navigation simulator. INTLAB, which is a reliable computing package, has been used to ensure the interval computation, see Rump (1999). A model of a highway-road segment has been selected as the test-scene. All the vehicles involved in simulations are modeled using tricycle kinematic. More details about the configurations and setups used for testing are shown in Table 3:

Table 3. Simulation setups

Parameter	Value
Sampling step	0.1 (s)
Sensors update time	0.01 (s)
Follower Embedded system delay	0.025 (s)
Leader maximum velocity	22.2 (m/s)
Follower maximum velocity	23 (m/s)

In a first test scenario, a white gaussian noise is injected in the navigation process exact measurements. Hence, the risk assessment is tackled through several ways of the TTC estimation. Figure 4 compares results of the proposed set-membership TTC before/after proceeding the optimization step. In addition to outputs of the proposed set-membership TTC, Figure 5 exhibits results of the exact TTC (obtained through equation (2)), which is approximated without injecting any noise to the measurements.

Aside from the difference in the uncertainty level, the overall results show the same global behavior. The simulation starts with an initial inter-distance of $9.5m$, separating the ACC-equipped vehicle and an in-front car. Thus, the follower approaches steadily to the leader. The remaining time to collision is steadily dropping relatively to the decrease in the inter-distance. After few seconds, the inter-distance as well as the TTC are approximatively maintained stable since the ACC system ensures the respect of a reference distance. Several fluctuations in the presented results are entailed by the jerk i.e., a non smooth change in motion due to sudden bounding between acceleration/deceleration. This latter is not considered in this work.

As illustrated in Figure 4, the supervision of the correlation has effectively diminished the TTC uncertainty extent. Compared to the TTC initial over-approximation, the optimization step has provided a widely more optimistic risk prediction. The initial TTC enclosure has been reduced with average range of 60.4%. More importantly, Figure 5 shows that the exact TTC values are perfectly enclosed between the introduced set-membership TTC bounds. This fact means that the upper/lower security threshold values have been appropriately defined by the interval-based risk management approach.

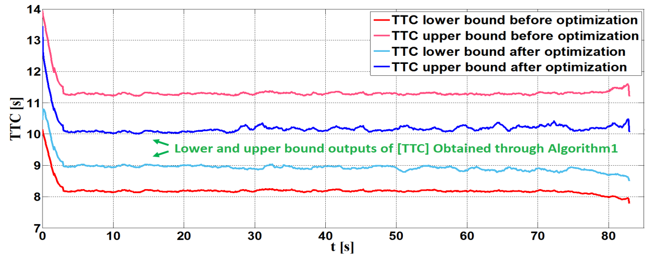

Fig. 4. TTC enclosures with/without the optimization step

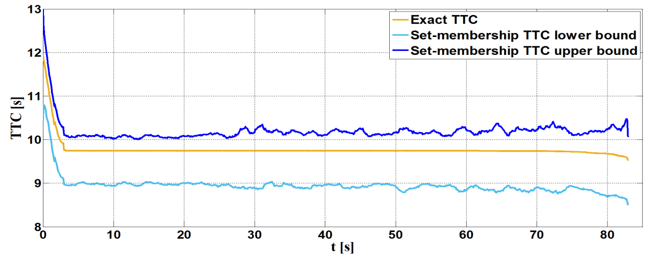

Fig. 5. TTC enclosures compared with exact results

To interpret in a better way the proposed approach aptitudes in handling the uncertainty, another test scenario is tackled. More sever uncertainty amounts are injected in the simulation measurements at different periods (P_1, P_2, P_3 and P_4). Uncertainties of 0.03 m/s, 0.06 m/s, 0.12 m/s and 0.18 m/s have been respectively injected for these periods in V_i. In practice, such uncertainties may be entailed by erroneous V2V communication or faulty sensor behaviors. Figure 6 illustrates this test-scenario results.

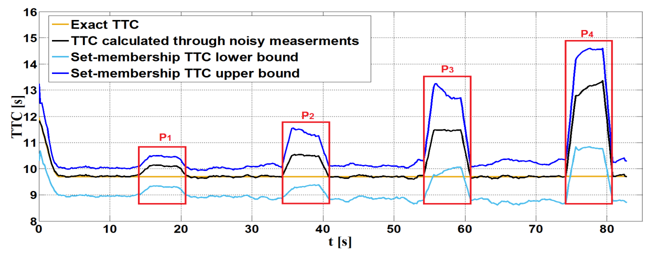

Fig. 6. Results with high uncertainty injection

Results of the deterministic TTC calculation (obtained using single-valued noisy measurements) are compared with the interval-based results. With respect to the vehicle's relative velocity, Table 4 illustrates the error in the reference distance given by each method relatively to the real d_{ref} that must be kept between vehicles.

The obtained results prove the efficiency of the proposed risk management strategy. The risk has been entirely mastered or at least considerably mitigated. Contrarily to existent approaches, the proposed interval-based uncertainty characterization method does not require any linearization. It allows also the risk management level to appropriately define min/max security thresholds.

Table 4. Error impacting d_{ref}

	P_1	P_2	P_3	P_4
Average of error in d_{ref} for deterministic computing (m)	-0.385	-0.631	-1.435	-2.753
Average of error in d_{ref} for set-membership computing (m)	+0.324	+0.171	-0.319	-0.833

6. CONCLUSION

This paper introduced a novel TTC interval extension. A set-membership risk management has been developed for an ACC system to face the uncertainty related challenges. The idea behind the proposed extension is to assess the risk with respect to the navigation surrounding environment. The vehicular communication latencies have been also considered. To avoid too conservative results, the uncertainty assigned to each measurement evaluated per interval has been reduced by monitoring the correlation between variables. Further, the obtained uncertainty amounts are implied explicitly on the TTC computation. Through the set-membership computation, the threats worst-case analysis is allowed. Relatively to the worst-cases of risk, the ACC control units maintains a safe and optimistic reference distance to an in-front vehicle. The efficiency of our proposition is validated through simulation results.

As a future work, the proposed approach should be integrated on a real vehicle. In addition, the set-membership TTC should be extended to cover more critical in-road maneuvers such as lane change.

ACKNOWLEDGEMENTS

The present work is supported by the WOW (Wide Open to the World) program of the CAP 20-25 project. It receives also the support of IMobS3 Laboratory of Excellence (ANR-10-LABX-16-01).

REFERENCES

Adouane, L. (2016). *Autonomous Vehicle Navigation: From Behavioral to Hybrid Multi-Controller Architectures*. Taylor & Francis CRC Press, ISBN: 9781498715584, 228 pages.

Chen, C., Xiang, H., Qiu, T., Wang, C., Zhou, Y., and Chang, V. (2018). A rear-end collision prediction scheme based on deep learning in the internet of vehicles. *Journal of Parallel and Distributed Computing*, 117, 192–204.

Dahmane, Y., Abdrakhmanov, R., and Adouane, L. (2018). Stochastic mpc for optimal energy management strategy of hybrid vehicle performing acc with stop&go maneuvers. *IFAC-PapersOnLine*, 51(9), 223–229. 15th IFAC Symposium on Control in Transportation Systems CTS 2018, Savona, Italy.

Dey, K.C., Rayamajhi, A., Chowdhury, M., Bhavsar, P., and Martin, J. (2016). Vehicle-to-vehicle (v2v) and vehicle-to-infrastructure (v2i) communication in a heterogeneous wireless network performance evaluation. *Transportation Research Part C: Emerging Technologies*, 68, 168–184.

Funfgeld, S., Holzpfel, M., Frey, M., and Gauterin, F. (2017). Stochastic forecasting of vehicle dynamics using sequential monte carlo simulation. *IEEE Transactions on Intelligent Vehicles*, 2(2), 111–122.

Gueddi, I., Nasri, O., Benothman, K., and Dague, P. (2017). Fault detection and isolation of spacecraft thrusters using an extended principal component analysis to interval data. *International Journal of Control, Automation and Systems*, 15(2), 776–789.

Hou, J., List, G.F., and Guo, X. (2014). New algorithms for computing the time-to-collision in freeway traffic simulation models. *Computational Intelligence and Neuroscience*, 2014, 1–8.

Iberraken, D., Adouane, L., and Denis, D. (2018). Multi-level bayesian decision-making for safe and flexible autonomous navigation in highway environment. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 3984–3990, Madrid, Spain.

Jaulin, L., Kieffer, M., Didrit, O., and Walter, E. (2001). *Applied Interval Analysis with Examples in Parameter and State Estimation, Robust Control and Robotics*. Springer, London.

Lakhel, N.M.B., Nasri, O., Gueddi, I., and Slama, J.B.H. (2016). Sdk decentralized diagnosis with vertices principle component analysis. In *2016 International Conference on Control, Decision and Information Technologies (CoDIT)*, 517–522, St. Julian's, Malta.

Naufal, J.K., Camargo, J.B., Vismari, L.F., de Almeida, J.R., Molina, C., Gonzlez, R.I.R., Inam, R., and Fersman, E. (2018). A2cps: A vehicle-centric safety conceptual framework for autonomous transport systems. *IEEE Transactions on Intelligent Transportation Systems*, 19(6), 1925–1939.

Nicola, J. and Jaulin, L. (2018). *Comparison of Kalman and Interval Approaches for the Simultaneous Localization and Mapping of an Underwater Vehicle*, 117–136. Springer International Publishing, Cham.

Noh, S. and An, K. (2018). Decision-making framework for automated driving in highway environments. *IEEE Transactions on Intelligent Transportation Systems*, 19(1), 58–71.

Park, H., Oh, C., Moon, J., and Kim, S. (2018). Development of a lane change risk index using vehicle trajectory data. *Accident Analysis & Prevention*, 110, 1–8.

Rump, S. (1999). INTLAB - INTerval LABoratory. In T. Csendes (ed.), *Developments in Reliable Computing*, 77–104. Kluwer Academic Publishers, Dordrecht.

Tan, H.S. and Huang, J. (2006). Dgps-based vehicle-to-vehicle cooperative collision warning: Engineering feasibility viewpoints. *IEEE Transactions on Intelligent Transportation Systems*, 7(4), 415–428.

Wang, S., Wang, W., Chen, B., and Tse, C.K. (2018). Convergence analysis of nonlinear kalman filters with novel innovation-based method. *Neurocomputing*, 289, 188–194.

Ward, J.R., Agamennoni, G., Worrall, S., Bender, A., and Nebot, E. (2015). Extending time to collision for probabilistic reasoning in general traffic scenarios. *Transportation Research Part C: Emerging Technologies*, 51, 66–82.

Xia, B., Shang, Y., Nguyen, T., and Mi, C. (2017). A correlation based fault detection method for short circuits in battery packs. *Journal of Power Sources*, 337, 1 – 10.

View publication stats