Interval-based/Data-driven Risk Management for Intelligent Vehicles: Application to an Adaptive Cruise Control System

Nadhir Mansour Ben Lakhal[1,2], Lounis Adouane[1], Othman Nasri[2] and Jaleleddine Ben Hadj Slama[2]

Abstract— **In this work, a novel interval-based/data-driven safety verification technique is introduced for Intelligent/Autonomous Vehicles (I/AV). The interval arithmetic is adopted to enhance the reliability of the analytical models used for the autonomous navigation. Furthermore, a data-driven technique, which monitors the correlation relating variables of the modeled system, is adopted to ameliorate the uncertainty assessment. In such a manner, tight bounds of safety margins are obtained. To provide reliable safety verification, the proposed risk management approach has been integrated on an Adaptive Cruise Control (ACC) system. It permits to detect erroneous uncertainty estimation of an Extended Kalman Filter (EKF). Simulation results prove the overall risk management efficiency and its ability to handle uncertainties.**

I. INTRODUCTION

Aiming to improve mobility, efforts have been drastically spent during the past decades to develop a new generation of Intelligent/Autonomous Vehicles (I/AV) [1]. However, the reliability of these establishments remains an important challenge [2]. To avoid serious damages and handle the situational/environmental risk, the I/AV community has focalized more attention on the safety verification and risk management techniques [3]. Accordingly, the hazard assessment level acquires data from the environment to capture risks. In such a way, the intelligent vehicle connectivity with its environment has been enhanced. The I/AVs have been equipped with plenty of advanced perception and communication tools. Smart cameras, Light Detection And Ranging (LiDAR), Dedicated Short Range Communications (DSRC) and Internet of Things (IOT) are concrete instances of these systems [4]–[7]. Nevertheless, the performances of such processes are prone to important uncertainties. Indeed, the navigation environment is an over-changing scene, where it is very hard to predict the road participant behaviors. Ignoring the uncertainties in measurements and other vehicle potential dangerous motions leads to unavoidable fail of the risk management and safety verification levels.

In this context, two distinct categories of uncertainty assessment and risk management approaches have been widely developed in the literature. A first part from the I/AV community has recourse to a set of model-based techniques to ensure a reliable navigation. This class of approaches relies on a deep understanding of the system behavior. Based on this understanding, vehicle's motions and the uncertainty evolution have been described analytically through mathematical models [8]. In general, these models are joined with a probabilistic forecasting to estimate event's occurrence and behaviors of nearby cars in the short term horizon [9]. The constructed model permits easily to verify and validate continuously the monitored system with a high robustness to uncertainties. A difference between the established model outputs and the real system performances pinpoints erroneous behaviors. However, elaborating high fidelity models to ensure reliable navigation is not so easy. Foremost, when dealing with multi-operational mode systems, applying model-based approaches is unrealistic [10]. Models are hopeless in reporting unpredictable and over-changing systems behaviors. Moreover, the cost imposed by the precise modeling in terms of time and effort is unacceptable.

Trying to adapt the safety verification techniques to the practical challenges, the interest has been intensively focalized on free-model approaches [11]. Data-driven methods have been introduced to characterize systems while skipping models formalization [12]. Instead of modeling the system behavior and its outputs under several conditions, more attention is given to the system historical properties. Compared to the model-based one, performances of the data-driven methods are in general more accurate. During the system modeling phase, formal methods apply frequently several simplifications for technical reasons. Especially in case of non-linear behaviors, such simplifications endanger the IA/V risk management level reliability [13]. Correspondingly, Machine Learning approaches, Bayesian Networks and Neural Artificial Networks have been successfully proceeded in this context [14]–[16]. The data-driven methodology extracts useful and relevant information by interpreting data structures and its statistical features. In that way, future trajectories of road participants have been efficiently predicted. Despite its simplicity and consistency, the data-driven methodology is useless when it is applied based on highly uncertain data. In that case, erroneous deductions may be reached.

As seen from the literature, the stated categories, applied in order to ensure reliable navigation, have various advantages and limitations. In this regard, a mutual execution of model-based and data-driven approaches can be useful to gather the best of their features. The main contribution of the present work is constructing a strong link between the data-driven and model-based techniques to provide a reliable, safe and flexible autonomous navigation. The robustness of the model-based techniques against uncertainty is improved through an interval-based representation of data. Therefore, the interval analysis ensures more accuracy for the estab-

The authors are with [1]Institut Pascal, UCA/SIGMA-UMR CNRS 6602, Clermont Auvergne University, France

[2]LATIS Lab, National Engineering School of Sousse (ENISo), University of Sousse, BP 264 Sousse Erriadh 1023, Tunisia.

lished analytical models. In the meanwhile, a data-driven process is utilized to boost the uncertainty characterization by the statistical examination of the correlation relating variables. As a consequence, tight bounds of min/max safety thresholds are obtained. Once performances of formal model-based approaches (as Kalman filter) are not any more enclosed inside these bounds, safety is not guaranteed and countermeasures must be taken. An application of the entire interval-based/data-driven approach is detailed for a modern Adaptive Cruise Control system [17].

The rest of this paper is organized as follows: Section II details the proposed interval-based uncertainty assessment policy, which is dedicated to I/AV. Section III explains the introduced statistical correlation-based step in enhancing the set-membership estimation of uncertainties. Section IV describes the integration of the interval-based/data-driven safety verification technique into the risk management associated to an ACC architecture. Section V summarizes this work main contributions and discusses future work.

II. Improvement of Analytical Models with an Interval-Based Quantification of Uncertainties

As already mentioned, the majority of the model-based approaches are joined with a probabilistic prediction of the uncertainty propagation into the studied process [18]. However, probability consists in an approximative guess, which is based on estimating the chance of an event occurrence. Especially when it is estimated based on false assumptions, this guess may not be compliant with the reality [19]. Another vulnerability of the probabilistic reasoning lies in admitting a particular distribution of probability. In reality, a sudden and unpredictable change in the noise features may take place.

In this paper, the interval arithmetic is adopted to play as a cut off with the probabilistic estimation of uncertainties [20]. Several research studies have been dedicated to exploit the set-membership methodology in coping with issues related to the autonomous navigation. Several interval-based contributions have been depicted in the literature to ensure accurate localisation and positioning for vehicles [21], [22]. Multivariate diagnosis methods have been extended to handle interval-data in the aim to monitor modern vehicular systems [23]. The interval analysis has allowed the determination of reachable sets and future occupancy regions of smart vehicles [24]. A comprehensive comparison between probabilistic methods and the interval analysis-based uncertainty handling approaches for reliable navigation can be found in [25].

Indeed, the set-membership computation (representing data as intervals) is based on determining upper and lower bounds for the measurement's real values. The data standard representation has been extended to intervals [26]. The mathematical operations $(+,-,*,/)$ and the elementary functions $(sin, cos, \log, ...)$ have been also extended to handle interval-valued arguments [20]. Advanced algorithms have been developed to ensure numerical integration and differentiation of interval equations and to solve polynomials with interval coefficients [26]. In such a manner, the uncertainty evolution is easily evaluated all along any algorithm of a given analytical model. The set-membership computation is assumed as guaranteed and reliable since the exact value of data is enclosed inside an interval bounds. To summarize, interval analysis has provided a strong enhancement for the constructed model's reliability. Augmented precision models have been obtained thanks to the set-theory. It helps to overcome limitations entailed by modeling imperfections. Even more, unlike existent uncertainty assessment approaches, the interval-based uncertainty characterization method does not require any linearization.

In the sequel, $[a] = [\underline{a}, \overline{a}]$ designates a real interval. $\underline{a}$ and $\overline{a}$ are its lower and upper bounds. The interval's width underlines the uncertainty extent associated to $[a]$. Notably, it is important to adopt a relevant procedure to appropriately define bounds of each interval-measurement. A prior knowledge of the uncertainty bounds may be acquired through confidence intervals associated to sensor's measurements [24]. Otherwise, interval widths may be correlated with the environmental conditions, which emphasize the increase in uncertainty. The communication delays and any uncertainty source must be taken into account too. Consider a system of n inputs and m outputs, denoted respectively by $x_{i=1..n}$ and $y_{j=1..m}$. Figure 1 illustrates the set-membership modeling principle for this system.

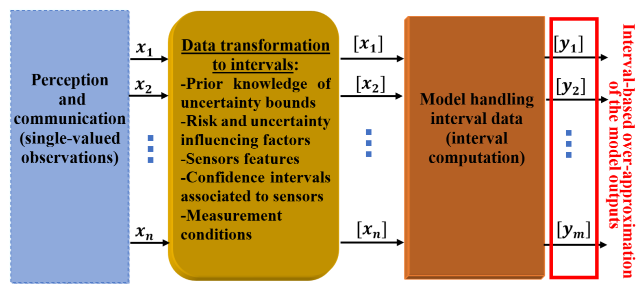

Fig. 1: Interval-based system modeling

Certainly, models accuracy is enhanced thanks to the interval arithmetic. The set-membership model provides over-approximations of findings that include without doubt exact values of outputs. For the safety and risk management levels, the interval-based modeling provides an efficient manner to perform the risk worst-case analysis. However, the obtained over-approximations are in general too conservative. To avoid degrading the autonomous navigation performances, the risk-management must balance between the safety and the accuracy requirements. To overstep this limitation, a data-driven optimization step is joined to the interval-based modeling. More tight and compact enclosers of the interval-based model outputs are reached by monitoring the correlation evolution.

III. Data-Driven Optimization Step

For optimality goals, the present section presents a data-driven optimization step, which is integrated into the interval-modeling phase. This step lays on a statistical characterization of the measurements. Dependencies between variables are exploited to characterize the navigation process and discard the over-estimated uncertainties. In statistics, the correlation coefficient is a common metric used to analyze the relationship between variables [27]. It is expressed as:

$$C_{X,Y|k} = \frac{COV_{X,Y|k}}{\sigma_X \sigma_Y} \tag{1}$$

Where $C_{X,Y|k}$ is the correlation coefficient assigned to variables X and Y at instant t_k. It is a real number, varying between $[-1,1]$. It reflects the strength of the linear relationship between X and Y. $COV_{X,Y|k}$ is the covariance associated to X and Y. σ_X and σ_Y are respectively their variances.

Plenty of reliability approaches and diagnosis processes are built based on monitoring the correlation [27]. The run-time characterization of system variable's dependencies is extremely efficient in this context.

A great part from the literature considers that a system correct behavior is validated through a smooth and progressive transition in the correlation states. Notably, in a very short sampling-time step, only the occurrence of abnormalities leads to a sudden important change in the correlation behavior [28]. Outliers, faulty measurements and radical change in the control system can entail such erroneous evolution of the correlation. This is the case for I/AVs studied in the present work. Mostly, a deep change in the navigation dynamics or in the surrounding circumstances is generally unrealistic in a short time horizon. In this sense, the run-time supervision of the correlation is adopted to refine results of the interval-based modeling of systems. Certainly, uncertainties attributed to each interval-measurement entail a deviation in the correlation compared to its original structure. Correspondingly, a more realistic prediction of the uncertainty evolution must ensure a minor fluctuation on the correlation between successive instants t_{k-1} and t_k. Based on this assumption, interval widths are recursively narrowed to guarantee an appropriate evolution of correlation between each couple of variables describing the behavior of a given system.

Basically, the correlation serves to perform dependency analysis of single-valued variables. In this work, a symbolic representation of intervals, namely the vertices transformation, is employed. It allows to calculate the correlation relating interval-valued variables and examine the uncertainty propagation into a given process. Let denote by X^I an interval data matrix, which is constructed by N observations describing M interval-valued variables $[x_{i|i=1..M}]$:

$$X^I = \begin{pmatrix} \left[\underline{x_1(1)}, \overline{x_1(1)}\right] & \cdots & \left[\underline{x_M(1)}, \overline{x_M(1)}\right] \\ \vdots & \ddots & \vdots \\ \left[\underline{x_1(N)}, \overline{x_1(N)}\right] & \cdots & \left[\underline{x_M(N)}, \overline{x_M(N)}\right] \end{pmatrix} \tag{2}$$

Indeed, the structure of a given interval observations of variables, can be geometrically interpreted as hyper-rectangle with a 2^M vertices (min/max bounds of intervals). Based on this idea, the vertices technique develops an equivalent single-valued matrix for X^I with the same initial data structure. The obtained single-valued matrix X^H, containing all the vertices and constructed from $N \times 2^M$ rows and M columns, is presented in the following shape:

$$X^H = \begin{pmatrix} \begin{pmatrix} \underline{x_1(1)} & \cdots & \underline{x_M(1)} \\ \vdots & \ddots & \vdots \\ \overline{x_1(1)} & \cdots & \overline{x_M(1)} \end{pmatrix} \\ \vdots \\ \begin{pmatrix} \underline{x_1(N)} & \cdots & \underline{x_M(N)} \\ \vdots & \ddots & \vdots \\ \overline{x_1(N)} & \cdots & \overline{x_M(N)} \end{pmatrix} \end{pmatrix} \tag{3}$$

It is important to notice that the vertices transformation does not impose any additionally computational complexity to the elaborated model. It depends exponentially on the value of the number M and linearly on the observations number N. In our case of study, M is always equal to 2 since the correlation coefficient evaluates the dependency between two distinct variables.

Once the equivalent single-valued data are obtained, it is possible to proceed to the correlation assessment for each couple of variables. Accordingly, the uncertainty minimization in the width of each measurement interval is done. 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}, denoted γ, is estimated through the following equation:

$$\gamma = C_{X,Y|k} - C_{X,Y|k-1} \tag{4}$$

Notice that 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.

Conditions 1 and 2 prohibit an over-narrowing of the interval-measurements. Without these conditions, the uncertainty amounts, affecting the navigation dynamics, may be under-estimated. Finally, the flow chart presented in Figure 2 recapitulates all the required steps to optimize results of the interval-based model. Together, the interval arithmetic and the data-driven characterization of uncertainties through the correlation construct a strong enhancement for the analytical formal navigation approaches. It should be noted that the obtained bounds are neither too conservative, nor optimistic thanks to the correlation supervision step. As it

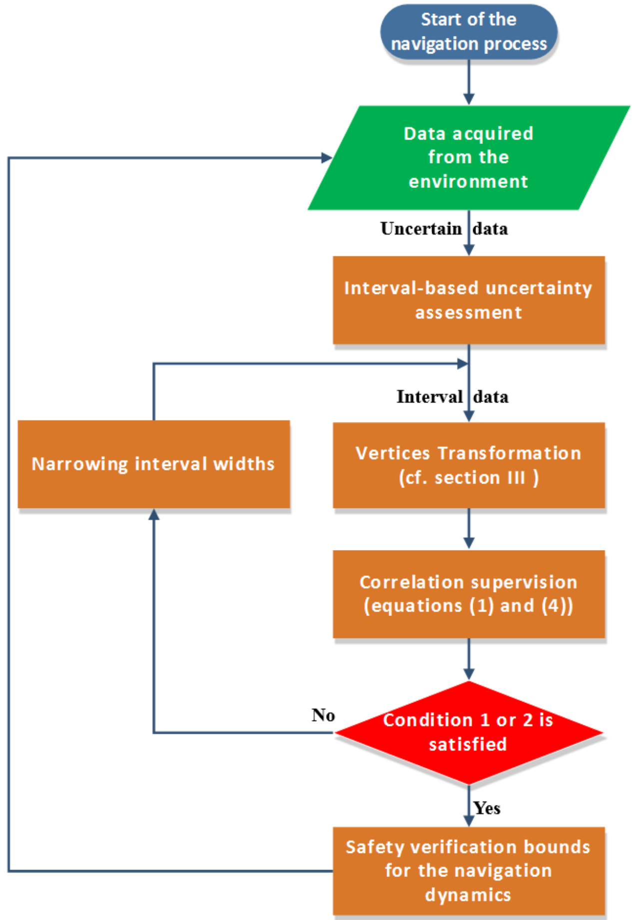

Fig. 2: Flow chart of interval-based/data-driven uncertainty modeling

will be explained in the next section, the obtained-bounds can play also as upper/lower safety margins. These margins are extremely useful in validating and verifying performances of the I/AVs risk management level. Aside from its reliability, the proposed strategy guarantee flexibility. Contrarily to the existing approaches, a specific point of the obtained interval may be selected by the risk management level based on a particular criterion.

IV. Application to an ACC System

As a proof of concept, the proposed interval-based/data-driven navigation approach is tested on an ACC system. It has as a main task to maintain a reference distance, denoted d_{ref}, from the in-front vehicle. d_{ref} is calculated in run-time in order to determine an appropriate target set-point for the ACC-equipped vehicle. The selected dynamic target must be characterized with a safe and acceptable Time To Collision (TTC) [29]. Indeed, the employment of the TTC as risk indicator is widespread for the autonomous transportation systems [14]. Using the interval arithmetic, $[TTC]$, $[d_{ref}]$ as well as an enclosure of the ACC-equiped vehicle target set point are determined in a set-membership manner.

In this case, a precise TTC formalization is given by the standard equation of motion, describing the displacements between the ACC-equiped vehicle and the in-front car. Consider two vehicles i and j with vector positions and velocities of: p_i, p_j, V_i and V_j respectively. Here, i and j indexes correspond respectively to the in-front vehicle and the ACC-equipped vehicle (cf. Figure 3). Hence, the study depicted in [30] has proved that the rate of change in the separation between i and j, denoted $\dot{d}_{ij}$, is expressed as:

$$\dot{d}_{ij} = \frac{1}{d_{ij}}(p_i - p_j)^T(V_i - V_j) \tag{5}$$

Where d_{ij} is the measured inter-distance separating i and j. Starting from equation (5) and by assuming a constant closure rate between vehicles, the TTC value may be obtained as follows [30]:

$$TTC = -\frac{d_{ij}}{\dot{d}_{ij}} \tag{6}$$

As already explained, a model, which handles interval data, is built based on equations (5) and (6). The obtained bounds of the established model findings will play an important role in validating the performances of an Extended Kalman Filter (EKF). For its reliability and efficiency the EKF, which is a stochastic model-based approach, is largely used to estimate and predict the vehicle's real states from sensor measurements. Despite its reliability, the EKF presents poor performances when the system is not properly conditioned [25]. Besides, the EKF outputs may converge to faulty estimations because of a sudden change in the statistical features of the noise affecting the navigation process. Hence, safety is guaranteed while the EKF outputs are enclosed between the tight bounds provided by the interval/data-driven based model. In the other case, the EKF model must be reconditioned and the system initial states have imperatively to be redefined. Figure 3 illustrates the principle of the suggested safety verification strategy for the ACC.

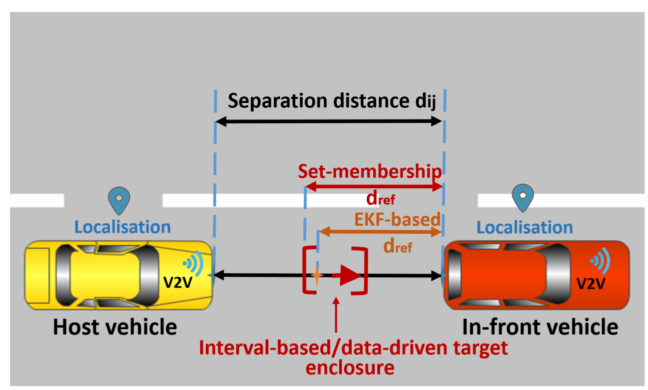

Fig. 3: Suggested ACC safety verification principle

To ensure the above explained strategy of the target set-point selection, a particular architecture with a risk management module, is designed. As shown in Figure 4, 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. In the meantime, an EKF is used simultaneously with the set-membership blocks in order to filter the measurements and compute the TTC in a stochastic way. According to the finding of the EKF as well the interval enclosures, instants where the EKF predictions diverge are detected. Finally, a control unit allows reaching the selected target with a desired orientation and velocity. Figure 4 illustrates the adopted architecture of the elaborated ACC.

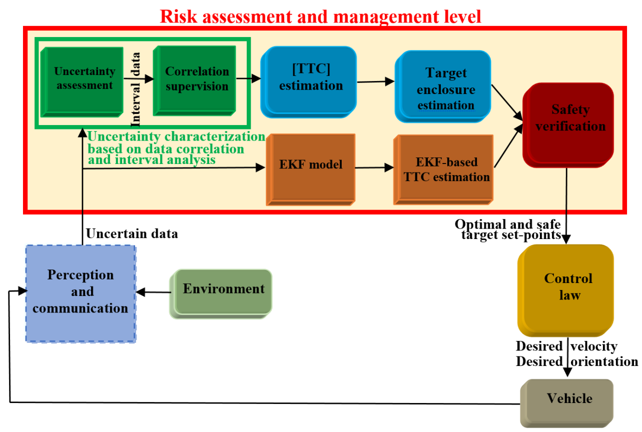

Fig. 4: Architecture of an interval-based/data-driven ACC

In the aim to validate the uncertainty assessment policy as well as the risk management, a freeway navigation Matlab simulator has been elaborated. The interval computation has been provided through the INTLAB package [31]. The simulated vehicles are modeled by the mean of tricycle kinematics.

A first test scenario is dedicated to evaluate the role of the correlation-based step in improving the risk management optimality. Figure 5 exhibits results of the set-membership modeling with/without proceeding the data-driven optimization step.

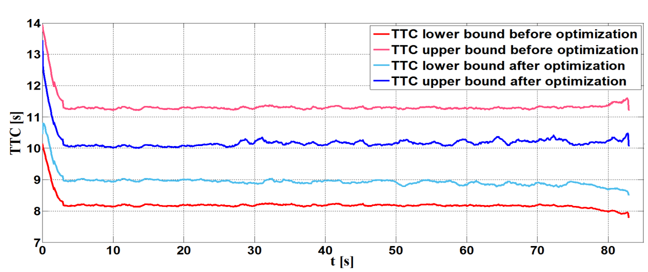

Fig. 5: TTC enclosures with/without the data-driven optimization step

As shown in Figure 5, the examination of the correlation has drastically reduced the width of the interval-valued TTC. Thanks to this optimization, the initial TTC enclosure has been reduced with an average range of 60.4%. For sure, a more realistic risk prediction has been ensured compared to the initial TTC over-approximation. Afterward, Figure 6 presents the evolution of the exact TTC. This latter underlines the TTC calculated in a deterministic manner (by equation (6) without injecting any noise in the simulation dynamics. The exact TTC is taken here as a reference to assess the consistency of the obtained results.

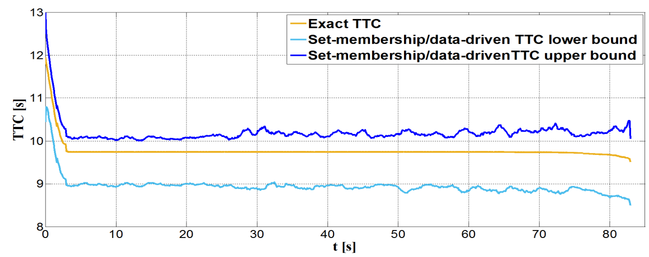

Fig. 6: TTC enclosures compared with exact results

Otherwise, Figure 6 demonstrates that the exact TTC values are perfectly enclosed between the introduced interval-based/data-driven TTC bounds. The upper/lower safety margins have been appropriately defined by the risk management approach. Finally, Figure 7 illustrates the safety verification process. The risk has been highlighted by red frames.

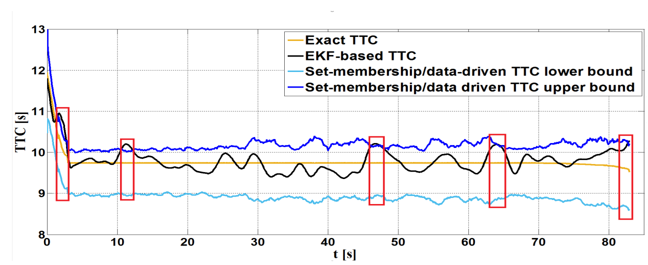

Fig. 7: Monitoring the EKF-based TTC through the interval-based/data driven margins

The obtained results prove the efficiency of the proposed risk management strategy. The risk has been entirely mastered through the detection of the EKF divergence instants. 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 safety thresholds.

V. Conclusion

The reliability and flexibility of the autonomous navigation approaches have been addressed in this work. In particular, a novel risk management/safety verification technique is introduced. Several uncertainties that may emphasize risks affecting the navigation process are characterized through the interval arithmetic. Accordingly, an over-approximation of variables, describing the navigation dynamics, is obtained. Inspired from data-driven techniques, the evolution of the correlation relating variables is characterized in the aim to refine the uncertainty assessment. As a result, tight bounds of the interval-valued dynamics leads to define min/max safety thresholds. The introduced interval-based/data-driven method has been joined with an EKF model to handle uncertainties into the navigation process. As a reliable safety verification technique, precautions must be taken once the EKF model-based approach diverges from the obtained bounds. Our suggestion ensures flexibility and optimality, since the safety set-points are represented by intervals. A selection of the most optimal setpoint, which is enclosed between the interval bounds may take place. The proposed risk management technique is applied on an Adaptive Cruise Control system. Simulation results prove the established risk management efficiency and its aptitude in handling uncertainties.

Even after proceeding the optimization step, the safety margins provided via the suggested method, may still a bit conservative. This issue will be handled in our future work. Otherwise, the proposed method should be integrated on a real intelligent vehicle.

ACKNOWLEDGMENT

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

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

[2] K. Kaur and G. Rampersad, "Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars," *Journal of Engineering and Technology Management*, vol. 48, pp. 87–96, 2018.

[3] H. M. Fahmy, M. A. A. E. Ghany, and G. Baumann, "Vehicle risk assessment and control for lane-keeping and collision avoidance at low-speed and high-speed scenarios," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 6, pp. 4806–4818, June 2018.

[4] H. S. Tan and J. Huang, "Dgps-based vehicle-to-vehicle cooperative collision warning: Engineering feasibility viewpoints," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 4, pp. 415–428, Dec 2006.

[5] K.-H. N. Bui and J. J. Jung, "Internet of agents framework for connected vehicles: A case study on distributed traffic control system," *Journal of Parallel and Distributed Computing*, vol. 116, pp. 89 – 95, 2018.

[6] Z. Rozsa and T. Sziranyi, "Obstacle prediction for automated guided vehicles based on point clouds measured by a tilted lidar sensor," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2708–2720, Aug 2018.

[7] A. Gupta and A. Choudhary, "A framework for camera-based real-time lane and road surface marking detection and recognition," *IEEE Transactions on Intelligent Vehicles*, vol. 3, no. 4, pp. 476–485, Dec 2018.

[8] C. Philippe, L. Adouane, B. Thuilot, A. Tsourdos, and H. Shin, "Safe and online mpc for managing safety and comfort of autonomous vehicles in urban environment," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, Nov 2018, pp. 300–306, Hawaii, USA.

[9] C. Wu, L. Peng, Z. Huang, M. Zhong, and D. Chu, "A method of vehicle motion prediction and collision risk assessment with a simulated vehicular cyber physical system," *Transportation Research Part C: Emerging Technologies*, vol. 47, pp. 179 – 191, 2014.

[10] O. Nasri, N. M. B. Lakhal, L. Adouane, and J. B. H. Slama, "Automotive decentralized diagnosis based on can real-time analysis," *Journal of Systems Architecture*, 2019.

[11] A. Khelifi, N. M. Ben Lakhal, H. Gharsallaoui, and O. Nasri, "Artificial neural network-based fault detection," in *2018 5th International Conference on Control, Decision and Information Technologies (CoDIT)*, April 2018, pp. 1017–1022, Thessaloniki, Greece.

[12] B. Jiang and Y. Fei, "Vehicle speed prediction by two-level data driven models in vehicular networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 7, pp. 1793–1801, July 2017.

[13] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniquespart i: Fault diagnosis with model-based and signal-based approaches," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 6, pp. 3757–3767, June 2015.

[14] D. Iberraken, L. Adouane, and D. Denis, "Safe autonomous overtaking maneuver based on inter-vehicular distance prediction and multi-level bayesian decision-making," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, Nov 2018, pp. 3259–3265, Hawaii, USA.

[15] Z. Deng, H. Sun, S. Zhou, J. Zhao, and H. Zou, "Toward fast and accurate vehicle detection in aerial images using coupled region-based convolutional neural networks," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 10, no. 8, pp. 3652–3664, Aug 2017.

[16] Z. Chen, C. Wu, Y. Zhang, Z. Huang, J. Jiang, N. Lyu, and B. Ran, "Vehicle behavior learning via sparse reconstruction with $\ell_2 - \ell_p$ minimization and trajectory similarity," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 2, pp. 236–247, Feb 2017.

[17] Y. Dahmane, R. Abdrakhmanov, and L. Adouane, "Stochastic mpc for optimal energy management strategy of hybrid vehicle performing acc with stop&go maneuvers," *IFAC-PapersOnLine*, vol. 51, no. 9, pp. 223–229, 2018, 15th IFAC Symposium on Control in Transportation Systems CTS 2018, Savona, Italy.

[18] A. Kasmi, D. Denis, R. Aufrere, and R. Chapuis, "Map matching and lanes number estimation with openstreetmap," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, Nov 2018, pp. 2659–2664, Maui, HI, USA.

[19] S. Noh and K. An, "Decision-making framework for automated driving in highway environments," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 1, pp. 58–71, Jan 2018.

[20] L. Jaulin, M. Kieffer, O. Didrit, and E. Walter, *Applied Interval Analysis with Examples in Parameter and State Estimation, Robust Control and Robotics*. Springer, London, 08 2001.

[21] H. Wang and A. Lambert, "A low-cost consistent vehicle localization based on interval constraint propagation," *Journal of Advanced Transportation*, vol. 2018, pp. 1–15, June 2018.

[22] A. L. E. F. K. Kueviakoe, Z. Wang and P. Tarroux, "Localization of a vehicle: A dynamic interval constraint satisfaction problem-based approach," *Journal of Sensors*, vol. 2018, pp. 1–12, Apr 2018.

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

[24] M. Althoff and J. M. Dolan, "Online verification of automated road vehicles using reachability analysis," *IEEE Transactions on Robotics*, vol. 30, no. 4, pp. 903–918, Aug 2014.

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

[26] R. Moore, R. Kearfott, and M. Cloud, *Introduction to Interval Analysis*, ser. Other Titles in Applied Mathematics. Society for Industrial and Applied Mathematics (SIAM, 3600 Market Street, Floor 6, Philadelphia, PA 19104), 2009.

[27] R. Han, S. Wang, B. Liu, T. Zhao, and Z. Ye, "A novel model-based dynamic analysis method for state correlation with ima fault recovery," *IEEE Access*, vol. 6, pp. 22 094–22 107, 2018.

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

[29] J. Vilca, L. Adouane, and Y. Mezouar, "Adaptive leader-follower formation in cluttered environment using dynamic target reconfiguration," in *Distributed Autonomous Robotic Systems*, N.-Y. Chong and Y.-J. Cho, Eds. Tokyo: Springer Japan, 2016, pp. 237–254.

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

[31] S. Rump, "INTLAB - INTerval LABoratory," in *Developments in Reliable Computing*, T. Csendes, Ed. Dordrecht: Kluwer Academic Publishers, 1999, pp. 77–104.