Interval-based Solutions for Reliable and Safe Navigation of Intelligent Autonomous Vehicles

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***Abstract*— The transportation systems reliability is addressed in this work. A comprehensive comparison between the probabilistic and the interval-based uncertainty handling approaches for autonomous navigation has been detailed. Based on this comparative study, a set-membership safety verification technique that monitors the correlation between variables has been proposed to achieve an optimal uncertainty assessment. Further, a Principle Component Analysis (PCA) diagnosis process has been extended to handle interval-data. Finally, a strong link between the proposed automotive diagnosis and risk management has been constructed to ensure a high robustness to uncertainty. The proposed interval-based solutions have been integrated on an Adaptive Cruise Control (ACC) system. Simulation results prove the proposed diagnosis and risk management efficiency in handling uncertainties and faults.**

I. INTRODUCTION

The past few decades have witnessed a tremendous increase in autonomy for modern navigation systems. For the sake of safety and comfort, numerous advanced navigation approaches have been introduced to improve the Intelligent Autonomous Vehicles (IAV) capacities [1]. The need for a reliable operation of IAVs is the most important result of the increase in autonomy. Multitude of risk management strategies have been developed for this context. Safety verification and risk involvement into the decision-making level of IAVs have become an active research field [2]. A proper risk-awareness requires an appropriate perception of road participants and a quick interaction with changes in the navigation environment. In this regard, the IAV community has boosted vehicle's connectivity to deal with safety anxieties [3]. Subsequently, a considerable literature is available for the research work related to accurate and efficient in-road obstacles detection [4]. In addition, several studies have been tackled to characterize the Vehicle-to-Vehicle (V2V) communication latencies and analyze their effects on the in-road safety [5]. Afterward, data captured by the perception-level need absolutely to be well-interpreted to succeed the situational risk assessment. In this context, focus has been given to formalize analytical metrics to ensure hazard analysis. The Time To Collision (TTC), the Distance To Collision (DTC) and the Time To React (TTR) are among the commonly utilized threat indicators [6].

Otherwise, the risk management strategies are hopeless in dealing with in-road threats in case of fault occurrence. Accordingly, it is crucial to provide any automotive system with Fault Detection and Isolation (FDI) components [7]. The diagnosis includes conventionally two main phases. Faults must be detected first in run-time. Besides, the deficiency source must be localized to make a final decision about the concerned system aptitudes in carrying its operation [8]. Nevertheless, the IAV diagnosis and risk management full reliability is not reached for yet. A considerable limitation of these methods is being sensitive to the modeling and the evaluation of uncertainties. Usually, the uncertainty propagation into the navigation system are estimated through stochastic/statistical approaches. Despite their widespread employment, it has been proven that performances of the probabilistic/statistical approaches are not guaranteed [9]. As a new emergent alternative, the interval analysis has been lately adopted to overcome inaccuracy threatening the IAV safety. Several contributions have been depicted in the literature from this perspective (cf. section II-B).

In this work, a comprehensive comparison between the interval and non-interval-based approaches in handling uncertainty has been detailed. Based on the state-of-the-art analysis, the interval analysis is efficient in providing robustness against uncertainty even though being too conservative. Accordingly, an optimal interval-based method to generate safety margins for intelligent vehicles is proposed. Besides, a statistical diagnosis approach, named Vertices Principle Component Analysis (VPCA), has been extended to handle interval-data [10]. Together the interval-based safety verification and diagnosis build a sound risk management level. Thanks to the interval analysis, a guaranteed estimation of uncertainty is provided. Moreover, contrarily to the existent literature and our previous work [11], [12], the proposed risk management ensures a fault-aware hazard situational assessment to reach a reliable navigation. A great complementary between the safety verification and the diagnosis has been created to better react against uncertainties and faults. The overall suggested risk management approach has been tested on an Adaptive Cruise Control (ACC) system [13].

The remaining of this work is arranged as follows: Section II exhibits the state-of-the-art and analyzes the interval-based approach performances. Section III introduces a statistical correlation-based step that aims to improve the set-membership estimation of uncertainties. Section IV describes the required steps to establish the adopted diagnosis process. Section V details the integration of the proposed interval-based solutions into the risk management level of an ACC system. Section VI recapitulates this work principle contributions and discusses future work.

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II. Interval vs. stochastic Uncertainty handling

The current section details the related work in coping with uncertainty in measurements and vehicle's dynamics. A concise comparison between the stochastic and the interval-based approaches, applied for this purpose, is delivered.

A. Formal stochastic techniques

The uncertainty handling has been carried frequently by a probabilistic model-based prediction of the uncertainty propagation into the navigation system [14]. In this case, a deep knowledge of the studied system and its all-potential futuristic constraints are required. The application of such methods requires to linearize the concerned system behavior to ensure that the noise process is still Gaussian. However, the linearization-related error inhibits ensuring a long term horizon prediction [15]. Besides, the elaborated forecasting is appreciated as non-deterministic since it is based on a chance estimation of an event manifestation. Numerous extensions of Kalman filters are concrete examples of these prediction-based approaches. A careful conditioning of the system initial states is mandatory to avoid poor performances [9]. Even in that condition, a sudden change in the noise features may happen [16].

Recently, more attention is given to the multi-simulation approaches in handling uncertainties and predicting vehicle's motions. The use of Monte Carlo is the most widespread in this context [17]. To reach a more relevant probabilistic guess, multiple simulations are simultaneously executed to take into account the variability in the system inputs and all probable states [18]. According to the density of simulation findings, a final decision about the prediction is taken. Chances to proceed a prediction that matches the reality is stronger. Remarkably, proceeding such a large number of simulations is costly in term of calculation time. Moreover, results differs from simulation execution to another even with identical configurations. These approaches remain time consuming, non-deterministic and sensitive to linearization.

To overstep imperfections entailed by linearization, other studies have recourse to a set of model-free and learning-based methods such as neural or Bayesian networks and deep learning [19], [20]. The major drawback of these approaches is their heuristic nature. One technique to improve these approaches reliability is taking in consideration more of details about the navigation environment such as weather conditions and the vehicle stability constraints.

B. Interval-based techniques

A great progress has been made lately to develop the interval analysis aptitudes in dealing with uncertainties [21], [22]. In such a manner, the uncertainty evolution is easily evaluated all along any algorithm. Hence, the set-membership computation is assumed as guaranteed and reliable since the exact value of data is enclosed inside interval bounds. In the prospect of guarantying a satisfactory level of accuracy, plenty of set-membership filtering techniques, which are based on an "prediction-correction" steps, have been introduced [23]. These filters present important opportunities to provide a guaranteed state estimation for navigation systems. Instead of using probability, these estimators exploit for instance the system observable dynamics and set-inversion to estimate a given system real states [24]. Accordingly, the interval filters are highly deterministic.

The interval-based reachability analysis is an another way to ensure prediction for vehicle motions. As outlined in [25], the uncertainty attributed to the interval-valued variables allows to capture all potential reachable sets of road participants for several control cycles. It has been proven also that with an appropriate characterization of interval widths, error issued from linearization and modeling imperfection can be mastered [25]. Afterward, there is an increasing trend of tackling trajectory computation of autonomous systems in a constraint satisfaction context [26]. In this respect, interval analysis permits to accurately define optimal and feasible control set points. Contrarily to the non-interval approaches, flexibility is guaranteed, since specific points from intervals, which are utilized to describe the navigation process, may be selected based on a particular criterion.

All the stated interval-based contributions can be categorized into two distinct classes. A first class of these methods consists in a numeric "branch and bound" computation [27]. Starting from initial domains, set-inversion techniques permit, in an iterative way, to bound exact solutions of a given analytical problem. Despite the accuracy presented by these algorithms, they are featured by an unpredictable calculation time. One more category of interval-based methods relies only on a prior knowledge of the uncertainty bounds. This knowledge is generally acquired through confidence intervals attributed to sensor's measurements [25]. It is important to notice that the uncertainty prior knowledge-based approaches provide usually over-approximations for a given algorithm findings. These interval-valued results enclose the outputs exact values. However, the obtained over-approximations are in general too conservative. A highly careful consideration of the uncertainty influencing factors is required at this stage.

It has been demonstrated also that proceeding diagnosis in a bounded error context, to consider variability in measurements, improves drastically the diagnosis accuracy [28]. It enhances the sensitivity to faults [29]. Accuracy and high sensitivity to faults are primordial key requirements for the automotive diagnosis. In the light of the already investigated literature, Table I illustrates a comparison between performances of the reviewed approaches. Aspects considered in the depicted comparison are the most important components from today's IAV requirements. Obviously, the interval-based approaches can deal with limitations raised from the probabilistic and/or heuristic nature of the formal non-interval methods. Despite their contribution in ensuring safety, the set-membership techniques are a bit conservative. Accordingly, the next section introduces an optimization step for the interval computation to deal with this issue.

III. Interval-based safety verification technique

The interval analysis offers new opportunities to enhance the autonomous navigation performances. Especially for the

TABLE I: Comparison between uncertainty handling approaches for IAVs

Navigation requirement	**Accuracy**	**Handling modeling imperfection**	**Safety**	**Optimality**	**Determinism**	**Low computational complexity**	**Long horizon prediction**
Probabilistic linear abstraction approaches	- -	- -	- -	+ +	-	++	- -
Probabilistic multi-simulation approaches	-	-	-	+ +	- -	- -	-
Probabilistic free-model/learning approaches	- -	+ +	- -	+ +	-	+	-
Branch and bound interval-based approaches	+ +	+ +	+ +	-	+ +	- -	+ +
Uncertainty prior knowledge interval approaches	+ +	+ +	+ +	- -	+ +	-	+

safety-verification and risk assessment, interval computation is a valuable tool to carry out the worst-case analysis of hazards. Nevertheless, the pessimism characterizing the conservative over-approximations proceeded by the interval analysis may lead to weak performances of the IAVs. A tight balance between safety and optimality is highly needed at this stage. In the current section, an optimization step is introduced to enhance the interval-based computation for the autonomous navigation. More tight enclosures of interval outputs are obtained thanks to the proposed approach. Dependencies between interval variables are employed to eliminate the over-estimated uncertainty affecting measurements. In particular, the correlation factor is a widely utilized statistical metric for assessing the relationship between variables [30]. Indeed, the correlation coefficient $C_{X,Y|k}$ between variables X and Y at instant t_k is expressed as follows:

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

Note that $COV_{X,Y|k}$ is the covariance associated to X and Y. σ_X and σ_Y are respectively their variances. Different reliability verification techniques and diagnosis systems are developed based on the idea of monitoring the correlation progress [30]. A system appropriate operation is noticed in general through a smooth evolution of the correlation states. During a single sampling step, alone a high level of uncertainty or fault occurrence can invoke a radical brutal change in the correlation [31]. This fact fits perfectly the autonomous navigation systems. In most of cases, a sudden change in the navigation dynamics is roughly unrealistic in a very short time horizon. Correspondingly, the real-time monitoring of the correlation is exploited in this work to discard additional uncertainties attributed to interval-measurements. In such a way, an unpredictable deviation in the correlation initial structure is avoided during the interval-based uncertainty characterization. Based on this understanding, an adequate prediction of the uncertainty progress must ensure a minimum of variation on the correlation between consequent instants t_{k-1} and t_k. Accordingly, interval widths are iteratively diminished to guarantee the adopted assumption.

The first step of the proposed method consist in giving an initial estimation of the uncertainty affecting variables. For the safety-critical autonomous driving, a consistent methodology to define bounds of each interval-measurement is of utmost importance. One possible idea to meet this requirement is to create a strong link between interval widths and the measurement environmental circumstances. Any factor, which may emphasize the raise in uncertainty, must be taken into account. For instance, the communication delays should be imperatively considered in this respect. In what follows, $[a] = [\underline{a}, \overline{a}]$ presents a real interval. $\underline{a}$ and $\overline{a}$ are its lower and upper bounds. The width of an interval, noted $w([a])$ and $w([a]) = \overline{a} - \underline{a}$, is the uncertainty extent assigned to a.

Conventionally, the correlation evaluates dependency relation-ship between single-valued variables. To make it handel interval data, a symbolic transformation of interval-data is proceeded before the beginning of the correlation calculation process. Since it uses all the min/max bounds of the interval-measurements, this transformation is called the vertices transformation. Consider X^I an interval data-matrix, which is built through N observations describing M interval-valued variables $[x_{i|i=1..M}]$:

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

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:

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

Noticeably, there is no additionally computational complexity resulting from the vertices transformation. This latter depends exponentially on M and linearly on N. In our case of study, M is always equal to 2 since the correlation estimation incorporates only two distinct variables.

As soon as the equivalent matrix is arranged, the correlation assessment is proceeded for each couple from the variables. Thereafter, the interval widths reduction of each measurement takes place. The interval with the largest width is concerned by the iterative narrowing. After that, the vertices transformation is practiced and the gap in the correlation between instants t_k and t_{k-1}, denoted $\gamma_{k|k-1}$, is estimated through the following equation:

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

The uncertainty reduction is aborted at two conditions:

- **Condition 1**: When $\gamma_{k|k-1}$ 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 narrowing will entail undesired modification in the data proper distribution.
- **Condition 2**: When $\gamma_{k|k-1}$ exceeds the minimum variation of correlation noticed in the system nominal behavior. This latter is characterized via off-line simulations.

It is important to notice that the picked-up bounds are neither too conservative, nor optimistic thanks to the correlation examination. Essentially, the produced bounds may play as inferior/superior safety margins. These margins are hugely convenient to validate the operational performances of IAVs.

IV. Interval-based diagnosis

Due to its privileges, the automotive industry pay more attention currently to the free-model diagnosis [32]. In particular, the Principle Component Analysis (PCA) is a diagnosis method, which relies only on monitoring the system inputs/outputs to detect abnormalities [33]. More interestingly, the PCA reduces wisely the dimensionality of the data representation space i.e, data are classified into principle and residual components [34]. In such a manner, only the most meaningful information can be held to report the system state. It is well known that constructing models for the complicated new IAVs is highly challenging. Since it drops the system modeling and exploits data in intelligent way, the PCA is appreciated as suitable for intelligent vehicles. Nevertheless, the accuracy is the most important requirement for the safety critical systems such as IAVs. Likely to the majority of the data-driven approaches, the PCA remains a noise-sensitive method. Accordingly, the PCA is extended in this work to handle interval data. Unlike the generalized PCA, VPCA ensures an enhanced fault sensitivity and robustness against imprecisions. In the sequel, a brief reminder about the VPCA steps is provided.

A. Implicit model extraction from interval-data

Consider an interval-data matrix that contains N samples of m interval-valued data. This initial data-set must be transformed, thanks to Vertices approach (cf. section III), to a single-valued data to proceed the standard PCA. A second data matrix $X \in [N \times 2^m, m]$ is obtained. With $N_1 = 2^m \times N$ rows, X can be simply expressed as:

$$X = \begin{pmatrix} x_1(1) & \cdots & x_m(1) \\ & \ddots & \\ x_1(N_1) & \cdots & x_m(N_1) \end{pmatrix} \tag{5}$$

Hence, Σ is the covariance matrix whereby the existing correlations between all the variables are characterized:

$$\Sigma = \frac{1}{N_1} X^T X \tag{6}$$

The correlation analysis begins by approximating the eigenvector matrix $P \in R^{m \times m}$, which is associated to Σ. Oppositely to the model-based diagnosis, the VPCA does not develop a system behavioral model. Rather, an implicit model, which reduces the data dimensionality and reports the dependencies between variables, is utilized. Faults are outlined once these relations are missed within a real operating process. Building an adequate correlation model necessitates an optimal choice of the principle components. Divers algorithms have been depicted for this purpose in the literature [35]. Only the Variance of the Reconstruction Error (VRE) technique is addressed in this work [36]. The number of principle components l is estimated through the variance computation. The main idea behind the VRE is to admit $l \in [1, \cdots, m-1]$ that guarantee a minimum average of variance between variables. Recognizing the parameter l permits to decompose P. Hence forward, $\hat{P}$ and $\tilde{P}$ designate respectively the principal and the residual spaces assigned to P. Equation (7) highlights dimensions of the new spaces raised from the decomposition:

$$P = \begin{bmatrix} \hat{P}_{[m \times l]} & \tilde{P}_{[m \times (m-l)]} \end{bmatrix} \tag{7}$$

B. Fault detection

Indeed, the VPCA fault detection is ensured through the approximation of statistical indexes. Abnormalities are encountered once an index exceeds its predefined threshold. Table II summarizes each index formalization and its corresponding threshold.

TABLE II: Detection indexes and their associated thresholds

Index	**Formalization**	**Threshold**
Squared Prediction Error (SPE)	$x(k)(I - \tilde{P}\tilde{P}^T)x(k)^T$	$\delta^2_\alpha = g\ \chi^2_{h,\alpha}$
Squared Weighted Error (SWE)	$x(k)(\tilde{P}\tilde{\Lambda}^{-1}\tilde{P}^T)x(k)^T$	$\mathscr{T}^2_{H\alpha} = \chi^2_{(m-l),\alpha}$
Hotelling Index	$x(k)(\hat{P}\hat{\Lambda}^{-1}\hat{P}^T)x(k)^T$	$\mathscr{T}^2_\alpha = \chi^2_{l,\alpha}$
Mahalanobis Distance	$x(k)(P\Lambda^{-1}P^T)x(k)^T$	$\mathscr{D}_\alpha = \chi^2_{m,\alpha}$

Note that $k = 1..N \times 2^m$ and Λ is the eigenvalue matrix associated to Σ. $\mathscr{G}$ is the sum of λ_j, which are the eigenvalues of Σ. χ is the chi-square distribution function and α is the freedom degree parameter that is assigned for this latter. Afterwards, $\mathscr{G}$and h are calculated as follows:

$$\begin{cases} \theta_i = \sum_{j=l+1}^{m} \lambda_j^i \\ h = floor(\theta_1/\theta_2) \\ g = \theta_1/\theta_2 \end{cases} \tag{8}$$

C. Fault localisation

In the case of a fault occurrence, the examination of its origin is triggered. The present work utilizes the variable reconstruction method to identify the faulty sources. By considering that each variable is faulty, this technique achieves an entire reconstruction to measurements using the VPCA implicit model. Consider X_R the reconstructed vector associated to one variable from the initial data-set matrix. Ξ_R is the vector that underlines the reconstruction direction.

At an instant k, the principal part from X_R, denoted $\hat{X}_R$,is obtained through the following relations:

$$\begin{cases} \hat{X}_R = G_R X \\ G_R = I_m - \Xi_R(\tilde{\Xi}_R^T \tilde{\Xi}_R)^{-1} \tilde{\Xi}_R^T \\ \tilde{\Xi}_R = (I_m - \hat{P}\hat{P}^T)\Xi_R \end{cases} \tag{9}$$

Final decision about the fault source is obtained thanks to an isolation index $A_{SPE_R}(k)$. This latter is applied on the data resulting from the reconstruction:

$$A_{SPE_R}(k) = \frac{SPE_R(k)}{\delta_\alpha^2(k)} \tag{10}$$

Notice that $SPE_R(k)$ is calculated through the same formalization of the SPE index mentioned in the fault detection step (see Table II). By varying R from 1 to m, a faulty variable is pinpointed with an isolation index lower than 1.

V. Application to an ACC system

To present a proof of concept for the proposed interval-based solutions, simulations have been established on a modern ACC system. With no intention to be exhaustive in detailing its operation, the ACC takes safety measurements based on the instantaneous evaluation of the TTC [6]. Assuming that their dynamics remains constant in short horizon time, the TTC approximates the remaining period to a crash occurrence between two vehicles. Depending on the obtained TTC value, a reference distance to an in-front vehicle, noted d_{ref}, is maintained. The retained d_{ref}, must assure a longer TTC for the ACC-equipped vehicle for the next control cycle. In fact, the problem can be seen as a car-following scenario, where two vehicles i and j are represented respectively as the leader and the follower [37]. Consider V_i, V_j, p_i and p_j , which are both of vehicles velocities and positions. These dynamics are obtained at each instant thanks to sensor measurements and V2V communication. The TTC analytical formalization, proposed in [38], is adopted in this work since it fits the studied car-following scenario:

$$\begin{cases} TTC = -\dfrac{d_{ij}}{\dot{d}_{ij}} \\ \dot{d}_{ij} = \dfrac{1}{d_{ij}}(p_i - p_j)^T (V_i - V_j) \end{cases} \tag{11}$$

Where d_{ij} is the distance separating vehicles i and j and $\dot{d}_{ij}$ is the rate of change associated to this distance.

With a prior knowledge of uncertainty bounds in sensor's measurements, the $[TTC]$ as well as $[d_{ref}]$ are computed in real-time corresponding to the proposed uncertainty characterization method. After that, an encloser of the ACC-equipped vehicle target set-point is approximated via $[d_{ref}]$. The obtained enclosures have as a main mission to validate the couple $(TTC,\ d_{ref})$, which are calculated through a non-interval methods. As long as $(TTC,\ d_{ref})$ are perfectly enclosed by $([TTC],\ [d_{ref}])$ the navigation safety is guaranteed.

However, the uncertainty may exceed its normal bounded level in presence of anomalies. Especially in case of permanent fault occurrence, erroneous safety margins would

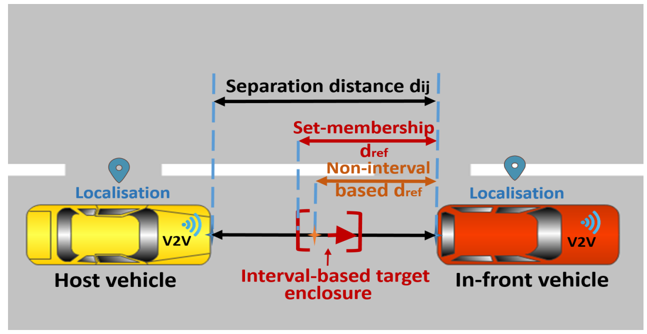

Fig. 1: Proposed ACC safety verification principle

be delivered by the set-membership uncertainty handling approach. Under these circumstances, the risk management becomes useless and the ACC-equipped vehicle safety is endangered. For this reason, all sensors and the communication tools are monitored through the proposed VPCA diagnosis process (represented respectively by p_i, p_j, V_i, V_j and d_{ij}). Hence, a fault-aware risk management strategy is provided through the mutual operation of the uncertainty handling and the diagnosis system. Once a fault is detected, warnings are delivered to the risk management level. Thus, the worst case of hazard is admitted and the ACC operation should be aborted. To establish this complementarity between the diagnosis and the uncertainty handling methodology, a specific multi-controller architecture [39] has been designed in order to perform reliable ACC. Figure 2 illustrates the elaborated architecture and its different components.

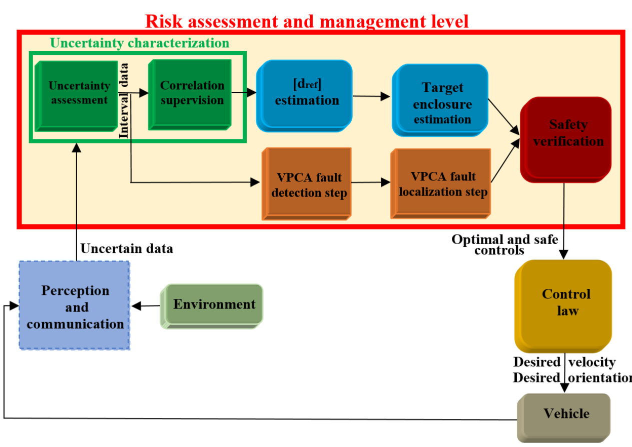

Fig. 2: Control architecture of interval analysis-based ACC

To validate the proposed interval-based approaches, a highway navigation Matlab simulator has been developed. The interval computation has been allowed thanks to the INTLAB package [40]. A first test scenario has been carried to highlight the role of the correlation-based step. Figure 3 illustrates results of the set-membership process with/without the optimization step.

As shown in Figure 3, the correlation supervision has notably diminished the width of the TTC enclosures. The un-

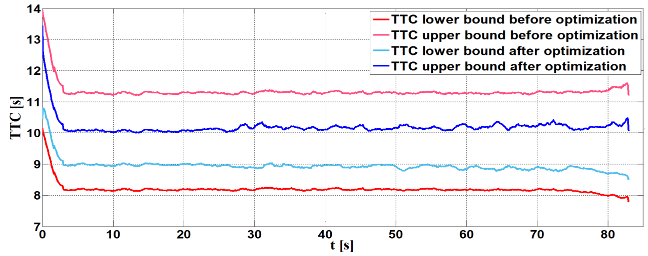

Fig. 3: TTC enclosures with/without optimization step

certainty evaluated in the TTC over-approximation has been reduced with an average rate of 60.4%. Monitoring the correlation has contributed in boosting the set-membership risk management optimality. In addition, all along the simulation run-time, the new compact TTC over-approximation encloses perfectly the exact TTC i.e., TTC calculated without injecting any noise in the simulation dynamics. Consequently, the upper/lower safety margins have been appropriately defined by the risk management approach.

During a second test scenario, huge random uncertainty amounts have been injected in the simulation measurements at three different periods. More precisely, such enormous uncertainties, which may only occur in case of fault presence, have been injected in V_i measurements. Figure 4 presents the evolution of the SPE detection index applied to monitor the ACC system. As shown, anomalies have been well-detected and the SPE index has exceeded its associated threshold during fault injection instants.

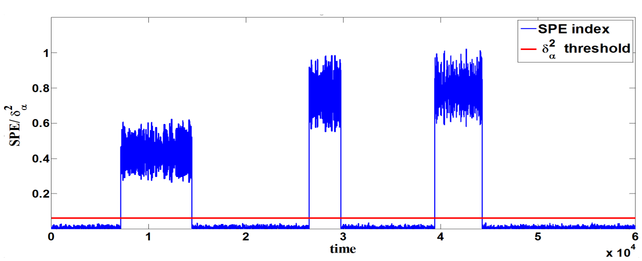

Fig. 4: Fault detection with SPE index

Once a fault is detected, the fault localisation step is triggered. Figure 5 presents the evolution of the A_{SPE_R} isolation index, which is computed after the reconstruction of each variable at the first time a fault is detected.

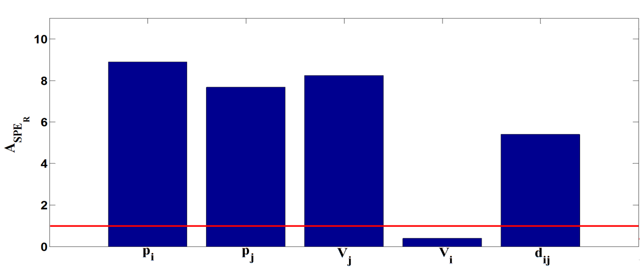

Fig. 5: Fault isolation with A_{SPE_R} index

The depicted results confirm that the communication tool, which is responsible for providing the leader velocity V_i, is the fault source. Simulations prove the efficiency of the proposed risk management within its associated diagnosis process. The uncertainty-related risks as well as faults affecting sensors and the communication tools have been detected and well-mastered.

VI. Conclusion

A comparative study between performances of uncertainty handling approaches, which are dedicated for IAV safety verification, has been presented. It has been deduced that the interval-based methods has great aptitudes in ensuring accuracy and robustness to uncertainty. However, these approaches are too conservative in general. To solve this problem, the evolution of the correlation relating variables is characterized to refine the uncertainty evolution assessment. Compact enclosures, obtained via the interval arithmetic, supply min/max safety thresholds. An efficient hazard worst-case analysis is permitted via these enclosures. The proposed risk management includes also a PCA-based diagnosis process, which handles interval-data. A tight link between the uncertainty handling and the diagnosis has been established to ensure a reliable autonomous navigation. The overall risk management technique has been integrated on an ACC. Simulation results prove the elaborated safety verification-level efficiency and its aptitude in handling uncertainties.

Further work intends to integrate a "prediction-correction" step into the set-membership safety verification method. Otherwise, the proposed risk management should be integrated on a real intelligent vehicle.

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