Adaptive Fault Detection exploiting Redundancy with Uncertainties in Space and Time

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Abstract. The Internet of Things (IoT) connects millions of devices of different cyber-physical systems (CPSs) providing the CPSs additional (implicit) redundancy during runtime. However, the increasing level of dynamicity, heterogeneity, and complexity adds to the system’s vulnerability, and challenges its ability to react to faults. Self-healing is an increasingly popular approach for ensuring resilience, that is, a proper monitoring and recovery, in CPSs. This work encodes and searches an adaptive knowledge base in Prolog/ProbLog that models relations among system variables given that certain implicit redundancy exists in the system. We exploit the redundancy represented in our knowledge base to generate adaptive runtime monitors which compare related signals by considering uncertainties in space and time. This enables the comparison of uncertain, asynchronous, multi-rate and delayed measurements. The monitor is used to trigger the recovery process of a self-healing mechanism. We demonstrate our approach by deploying it in a real-world CPS prototype of a rover whose sensors are susceptible to failure.

Index Terms—fault detection, self-healing, cyber-physical systems, redundancy model, observation model

I. INTRODUCTION

Cyber-physical systems (CPSs) are desired to be resilient (i.e., dependable and secure) against different kinds of faults throughout its lifecycle. Failure scenarios like communication crashes and dead batteries (fail-silent, fail-stop) are easy to handle (watchdog/timeout). However, sensor data may be erroneous due to noise (e.g., communication line, aging), environmental influences (e.g., dirtying, weather) or a security breach. To detect a sensor failure one has to define a valid signature [6]–[8], [21] or specification [3], [12] or create particular failure models [5], [17] for each possible hazard (e.g., aging, dirtying and a security breach). A simple method for detecting a faulty sensor value in different failure scenarios is to check against related information sources, i.e., exploit redundancy. Explicit redundancy, that is replicating the sensor [18], [24] is costly.

A designed system might not incorporate (implicit) redundancy straightaway (if so, the system would use information fusion to exploit the redundancy). However, when assembling (sub-)systems of different suppliers redundancy often becomes available. This is typically the case for distributed systems like the Internet of Things (IoT) or a CPS. For instance, the drivetrain of an electric vehicle is equipped with several sensors at the battery, motor, transmission, shaft, differential, or wheels level. The physical entities (CPS variables) observed in these subsystems, e.g., power consumption, revolution, speed or torque, are all related to the velocity of the vehicle, thus providing implicit information redundancy [1], [16].

We exploit such implicit redundancy by encoding it in a knowledge base [16], [28] created by domain experts or learned during runtime. Our previous work [27], [28] shows how to setup and use the knowledge base to substitute failed observation components. We refer to it as Self-Healing by Structural Adaptation (SHSA). However, SHSA requires a monitor to trigger the recovery from failures.

This work exploits the SHSA knowledge base to monitor related information. Similar solutions [22], [23], [32] perform the comparison synchronously, that is, all measurements are assumed to have the same timestamp (and therefore can be safely compared against each other). However, typically the runtime monitor has to cope with asynchronous, multi-rate and delayed measurements. Moreover, the timestamp of a measurement might not express the time when the CPS variable actually adopted this value (time-delay system). Typical runtime monitors are statically configured and therefore cannot cope with changes of an elastic and evolving system (e.g., availability of signals, message structure of the observations).

We therefore propose an observation model based on interval arithmetic considering uncertainties in space and time and an adaptive method to compare such signals. In particular, our novel contributions are as follows:

- A short, adaptive and extensible implementation of the knowledge base in Prolog/ProbLog.
- A simple model for observations of a signal that is prone to uncertainties in space and time.
- The generation of adaptive runtime monitors for signals which compare uncertain, asynchronous, multi-rate and/or delayed observations.
Demonstration of our method on a real-world application – an implementation on a rover prototype that performs collision avoidance.

The rest of the paper is organized as follows. Section II reviews the related work. Section III introduces the running example of our mobile robot and defines the knowledge base. Section IV encodes the knowledge base in Prolog and shows how to query for redundancies. Section V describes the observation model and presents how a monitor is generated for comparing items. Section VI demonstrates and tests the fault detection of the generated monitor. Section VII concludes by summarizing our results and outlining the future work.

II. RELATED WORK

In [16], Höftberger introduced an ontology (a knowledge base) defining physical relations or semantic equivalences between variables (e.g., laws of physics) to substitute failed observation services. We applied this technique in [27] and we extended the knowledge base with properties and utility theory in [28]. However, this knowledge base has been only exploited for failure recovery, but not yet for fault detection.

Literature on fault detection is spread to the area of runtime verification [3], [4], [12], anomaly detection [8], intrusion detection [6], [7], [21], fault-tolerance [2], [14], [18], [30] and self-healing [13], [25]. Approaches to detect faults typically use a specification or signature, an anomaly model or redundancy as a reference to judge the behavior of an entity.

A popular approach to perform fault detection in safety critical systems is to exploit redundancy of components. Examples include lockstep [24] and triple modular redundancy (TMR) [18] that explicitly replicate software or hardware components to detect faults. In the best case the replicas are diverse, i.e., they have been separately designed but share the same functionality and interface, to avoid joint or concurrent failures. Replication is generally expensive because it requires additional time and resources both at design time and runtime.

The security framework described in [10] performs anomaly detection on input signals of a component in a distributed network by comparing the input against trusted local signals (if available). The local signals may be provided by sensors which are directly sampled by the component and not advertised in the vulnerable communication network (cf. IoT) of the system.

The proposed method in [23] votes over signals sent through transfer functions (cf. relations) of known or unknown relationships of signals. The difference between the signals raises an alert when it exceeds a threshold. Similarly, we use transfer functions (here: relations) to bring signals into a common domain before comparison.

The author of [22] uses ensemble modeling to represent the redundancy of data streams. First a dependency graph between data streams of nodes is created (via cross-correlation). An ensemble of estimators of the learned models is defined given a threshold on the cross-correlation. The estimators can be created from different types of models (e.g., linear functions or neural networks) to relate the data streams to each other (temporal and functional relationships in the physical layer).

The output of the estimators are combined in a weighted-averaging fashion (cf. confidence-weighted averaging [11]). Another threshold for the estimator output defines whether an anomaly has occurred or not. However, the ensemble is statically defined during design time. The estimators have to be aggregated and weighted in a proper way. Similarly, the threshold is crucial to avoid false positives. Although time delays are not discussed, appropriate estimators can be set up to consider (at least constant) time delays.

The authors of [31] propose instead a Bayesian network (BN) with past and future values of sensor readings and redundant ones (spatial and temporal redundancy) to estimate the true state of a variable. A sensor is classified faulty, when its measurement exceeds a threshold given the estimated state. Similarly, fault injection is used to evaluate the monitoring technique. The proposed BN can be compared to a state estimator fusing redundant sensors.

| REFERENCES | REDUNDANCY | ADAPTIVE SYSTEMS | SPACE | TIME |
|------------|------------|------------------|-------|------|
| [18], [24] | ✓          |                  |       |      |
| [10]       | ✓          |                  | ✓     |      |
| [23]       | ✓          |                  |       | ✓    |
| [31]       | ✓          |                  |       | ✓    |
| [22]       | ✓          | ✓                | ✓     | ✓    |
| This work  | ✓          | ✓                | ✓     | ✓    |

This table compares state-of-the-art fault detection using redundancy.

All related work listed in Table I considers constant variance of the signals, i.e., the threshold for mismatch is set a priori. By using intervals to express observations we can handle time-varying errors. Most of the related work assumes the signals to compare to be sampled at the same point in time, i.e., are truly comparable. A dynamic BN like proposed by [31] could relate asynchronous observations to each other by forward estimation given the timestamp of the observation. However, neither of the listed work discussed this issue. Our knowledge base resembles a Bayesian network (in particular the sensor model of a BN), similar to [22], [31], but with deterministic nodes (relations or transfer functions) that can be re-used, merged and adapted when components are added or removed from a system. However, for our needs the knowledge base expresses a set of rules (cf. relations) on how to compare signals or to substitute a failed signal.

III. BACKGROUND

In this section we recap our knowledge base of redundancy and showcase it on a real-world prototype [28].

A. Running Example

The running example is a mobile robot (Pioneer 3-AT) that avoids collisions. Our rover under test (Fig. 1) is equipped with a Jetson TK1 and a Raspberry Pi 3 running the Robot Operating System (ROS) [26] and controlled via WiFi using a notebook. A ROS application can be distributed into several processes, so-called nodes which may run on different machines. Nodes communicate via a message-based interface.
of a CPS \( Z \) (cf. dynamic reconfiguration of an FPGA), we assume that each physical component comprises at least one software component \( z \) (e.g., the driver of the LIDAR) and henceforth, consider the software components only.

A system \( Z \) can be characterized by properties, referred to as system features, or simply as variables \( V \) (e.g., position of a vehicle, point cloud or distance measurements acquired by a LIDAR). In SHSA we focus on observations of CPS variables and refer to the actual data as value. A signal \( v(t) \) or short \( v \) represents the values of a variable \( v \) over time \((t \in \mathbb{R})\) provided by a certain component (e.g., a sensor).

The value of a system variable – an observation – is communicated between components typically via message-based interfaces. We denote such transmitted data representing the value of a variable \( v \), as information atom [19], short itom. In general, an itom is a tuple including data and an explanation of this data. An SHSA itom \( v(t_s) = (v(t_s), \text{timestamp}) \) is a sample or a snapshot of a variable at a certain point in time \( t_s \). It provides the following explanation of the data: i) the associated variable or entity, and ii) the timestamp of the acquisition or generation of the value. Each itom is identified by its signal’s name \( v \) and its timestamp. A variable can be provided by different components simultaneously (e.g., \( p \) redundant sensors).

Each software component \( z \) executes a program that uses input signals and provides output signals.

The CPS implements some functionality, a desired service (e.g., tracking). The subset of components implementing the CPS’ objectives are called controllers.

A signal \( v \) is needed, when \( v \) is input of a controller.

**Case Study** (Fig. 2): The rover is tele-operated by the controller \( z_{notebook} \) publishing the desired velocity \( v_{cmd} \). The distance to the nearest obstacle \( d_{min} \) is evaluated by the component \( z_{dmin_calc} \) using the LIDAR data as input. As soon as \( d_{min} \) falls below a safety margin (for simplicity a constant value) the robot’s verified desired velocity \( v_{safe_cmd} \) is set to zero. The component \( z_{rover_sc} \) applies \( v_{safe_cmd} \) to the motors and provides sonar range measurements \( v_{sonar} \) and actual linear and angular velocity \( v_{speed} \).

Another component \( z_{tof} \) provides 3D images of the environment in front of the rover. However, dashed signals in Fig. 2 are not used for collision avoidance but available for other tasks (e.g., parking, object recognition).

**C. Input Interface of Components**

The messages communicated within the network may be received synchronously or asynchronously. In our rover like in many other IoT infrastructures, the communication is asynchronous, i.e., the exact point in time of a message reception is unknown. The task of the component might be executed when an itom is received (e.g. \( z_{dmin_calc} \) calculating minimum distance when receiving \( v_{lidar} \)). However, the inputs of a software component might be published with different rates. Some components therefore have to cope with multi-rate, asynchronous and late messages. The monitor described in Sec. V periodically executes the plausibility check using the itoms collected since the last monitor call and a (configurable sized) buffer of itoms of previous executions.

**D. Knowledge Base of Redundancy**

This section defines the knowledge base used to describe implicit redundancy [28].

1) **Variables and Relations**: Variables are related to each other. A relation \( r : \mathbb{V} \rightarrow \mathbb{V} \) is a function or program (e.g., math, pseudo code or executable python code) to compute an output variable \( v_o \) from a set of input variables \( V_i \). The relations can be defined by the application’s domain expert or learned (approximated) with neural networks, SVMs or polynomial functions (see [27]).

2) **Structure**: The knowledge base \( K = (V, R, E) \) is a bipartite directed graph (which may also contain cycles) with independent sets of variables \( V \) and of relations \( R \) of a CPS, \( V \) and \( R \) are the nodes of the graph. Edges \( E \) specify the input/output interface of a relation. In particular, \( v_i \) is an input variable for \( r \) iff \( \exists r(v_i, r) \in E \) denoted as \( v_i \xrightarrow{r} r \). \( v_o \) is the output variable of \( r \) iff \( \exists (r, v_o) \in E \) denoted as \( r \xrightarrow{o} v_o \). \( Pred_j(x) \) denotes the predecessors of a node \( x \) in graph \( Y \).

There are no bidirectional edges, i.e., for \( v_j \neq i \) if \( r \xrightarrow{i} v_i \Rightarrow \overline{r} \xrightarrow{o} v_j \). Hence a variable is either input or output to a relation, but never both. A relation can further have only one output variable, i.e., for \( v_j \neq i \) if \( r \xrightarrow{i} v_i \Rightarrow \overline{r} \xrightarrow{o} v_j \). Note that relations have to be modeled as nodes, not edges, because a variable is typically related to more than one variable via a single relation.
Case Study: The application nodes of the rover (Fig. 2) provide several observation signals. The relations of the signals, that is the knowledge base, are set up manually (Fig. 3).

3) Substitution: A substitution $s$ of $v_{sink}$ is a connected acyclic sub-graph of the knowledge base with the following properties: i) The output variable is the only sink of the substitution (acyclic + Eq. 2), ii) Each variable has zero or one relation as predecessor (Eq. 3), iii) All input variables of a relation must be included (Eq. 4); it follows that the sources of the substitution graph are variables only.

$$s = (V_s, R_s, E_s)$$

$\forall x \in V_s \cup V_E \\forall y \in R_s \cup V_s \exists x \in E_s \exists y \in E_s \ (y \in R_s \vee y \in V_s) \ (\exists x \in E_s \ y \in E_s) \ (\forall v \in V_s \ | \exists x \in E_s \ y \in E_s) \ (\forall r \in R_s \ | \exists v \in E_r \ | v \in V_s)$

A substitution $s$ is valid if all sources are provided, otherwise the substitution is invalid. We denote the set of valid substitutions of a variable $v$ as $S(v)$. Only a valid substitution can be instantiated by concatenating the relations $R_s$ to the function $f$, which takes selected signals $I_s$ as input.

Case Study: When $v_{dmin}$ fails it can be replaced by the outputs of the substitution in Figure 4, by using the provided signal $v_{tof}$ as input.

IV. SHSA IN PROLOG

The knowledge base has been depicted as a graph and can also be implemented as such. Once encoded in a graph, it enables us to use existing efficient search algorithms. The substitution search can be implemented as a depth-first search [16]. In [28] we implemented a guided search that decreases the runtime of the substitution search. However, due to the optimizations and libraries used, the configuration of the knowledge base is difficult to read and the code base is quite large.

A Prolog program is a set of facts, rules and queries. Prolog’s central operation is unification, that is, the Prolog engine tries to make a query true. Prolog therefore implicitly enables the search for a substitution. Unlike the recovery, the setup of the runtime monitor, which is only performed on changes in the knowledge base, has no such tight timing constraints. Moreover, the formal definitions of SHSA given in Section III can be efficiently (that is, with a few lines of code) expressed in Prolog. Prolog is also a good basis to extend SHSA in future work, e.g., for the validation of requirements of substitutions. The Prolog engine used – ProbLog [9] – particularly provides a Python interface, enabling a smooth runtime adaptation of the knowledge base, making it easy to interface with existing applications, facilitating data (pre-)processing and taking advantage of a high-level programming language that overcomes the shortcomings of Prolog’s numerical capabilities. An interface to an interpretable language is also a requirement of SHSA (substitutions are searched and generated during runtime). The Python interpreter can evaluate arbitrarily complex code of a substitution.

A. Knowledge Base

The structure of the knowledge base and availability of variables is defined by a set of Prolog facts (see example in Listing 1). In particular, a relation $r: v_o = f(V_i)$ is written as the fact function($o,r,[i0,...,in]$) with a list of names $[i0,...,in]$ representing the input variables, a name of the relation $r$ and the name of the output variable $o$. An itom $i$ is available when the fact itom(i) evaluates to true. In addition, each itom has to be mapped to its corresponding variable. For convenience, the availability of a variable can be specified via a list of itoms, e.g., itomOf(v, [i0,...,in]). This implicitly maps each itom $i$ to the variable $v$ and marks the variable $v$ as provided(v) (provided is a Prolog property). The facts itomOf(.) are added during runtime to the program (structure of the knowledge base) depending on the itoms gathered by the monitor.

Case Study: Listing 1 shows the knowledge base of Figure 3 in Prolog. Table II maps the knowledge base variables to Prolog names.

Listing 1: Knowledge base of the mobile robot in Prolog.

```
:- use_module(library(shsa)).

% structure
function(dmin, r1, [d_2d]).
function(d_2d, r2, [d_3d]).
function(dmin, r3, [d_2d, speed]).
function(dmin_last, r4, [dmin]).

% provided itoms
itemsOf(dmin, ["/emergency_stop/dmin/data"]).
itemsOf(d_2d, ["/p2os/sonar/ranges", "/scan/ranges"]).
itemsOf(dmin_last, ["/p2os/cmd_vel", "/p2os/odom"]).

```

Table II: Used variable and signal names in Prolog.

| VARIABLE         | PROLOG SIGNAL            | PROLOG PROLOG |
|------------------|--------------------------|---------------|
| dmin             | dmin                     | "/emergency_stop/dmin/data" |
| v_{dmin}         | dmin_last                | "/emergency_stop/dmin/data" |
| v_{speed}        | speed                    | "/p2os/odom" |
| d_{2d}           | d_{2d}                   | "/p2os/sonar/ranges", "/scan/ranges" |
| v_{tof}          | v_{tof}                  | "/p2os/odom" |

B. Substitution Search

The Prolog library shsa implements a set of rules to evaluate properties (e.g., SHSA properties of variables like provided(v) ) or to search substitutions for a needed variable (query substitution(v,S) ). It basically implements the definitions in the previous section within 22 lines of code. Details can be found in our repository.

Finally, we can query properties, e.g., substitution(v,S) to find all valid substitutions

1https://github.com/dratasich/shsa-prolog
for the variable \( v \). The Prolog engine tries to satisfy the query, that is, it searches for \( S \) which evaluates the query to true (“unify” \( S \)) considering the given facts (SHSA knowledge base) and rules (SHSA library). In this case, \( S \) is a relation or a tree of relations, see the results of the substitution search for \( d_{\text{min}} \) in Listing 2.

The complexity of the query is the one of a depth-first search, i.e., \( O(b^d) \) with the branching factor \( b \) and depth \( d \) [28].

Due to the computational limits of Prolog, we parse the substitution results and execute the relations in Python. To this end, each relation is linked to an implementation capturing a string that can be evaluated in Python (Listing 3).

For instance, \( r_1 \) passes the distance measurements \( d_{2d}.v \) through the function it should implement, here: min. The timestamp \( d_{\text{min}}.t \) is adopted from the distance measurements to indicate the time when the minimum distance occurred.

V. FAULT DETECTION BY EXPLOITING REDUNDANCY

A generic monitor uses the knowledge base to setup a monitor for a given signal and to periodically compare against the related signals.

A. Setup and Adaptation

First, the monitor queries the valid substitutions \( S(v) \) given the variable \( v \) to monitor and the available signals (Sec. IV). Then the monitor parses the result and instantiates the substitutions. Once set up, the monitor periodically executes the substitutions with the given input itoms and compares the outputs against each other.

On system changes, e.g., regarding the relations or the availability of signals, the knowledge base can be adapted and the monitor re-initialized. For instance, the knowledge base may be extended with new relations whenever new information becomes available (i.e., when new observation components are connected to the system).

Case Study: The collision avoidance (controller \( z_{\text{safe}} \)) needs the signal \( v_{\text{dmin}} \) which shall therefore be monitored. The setup is depicted in Figure 5. This monitor compares the output of four substitutions (including the empty substitution using the itoms of signal \( v_{\text{dmin}} \) directly).
Note that our current implementation selects all substitutions possible for the monitor. However, the substitutions should be diverse. \( k \) faulty outputs of the substitutions can be identified when the number of comparable outputs is \( \geq 2k + 1 \) (majority) while assuming independent input itoms. For instance, faulty LIDAR data will cause mismatches in two substitutions \( s_1 \) and \( s_3 \) \((z_{\text{calc}} \text{ uses } v_{\text{lidar}} \text{ as input})\). Faults in \( v_{\text{lidar}} \) or \( v_{\text{dnsm}} \) therefore cannot be detected.

**B. Observation Model**

Once the observations or itoms are in the common domain, their values can be compared to each other. However, the values are uncertain, e.g., due to noise, interference or environmental conditions (the accuracy of a LIDARs distance measurement for instance is sensitive to the reflection capabilities of a surface).

In our proof-of-concept implementation we use simple integer arithmetic to express the allowed uncertainty of an itom or confidence into an itom. The value of the itom \( v(t_s) = (v, t_s) \) is expressed as an interval (Eq. 5).

\[
    v = [v, \bar{v}] = \{ v \in \mathbb{R}^2 | v \leq v \leq \bar{v} \} \tag{5}
\]

In real-world data, however, the itoms diverge not only in space but also in the time domain. This phenomenon is known as dead-time or aftereffect and occurs in time-delay systems [29]. Delays may accumulate from different sources, not only from communication latency. For instance, the travel of sound is slower than the travel of light. So the sonar sensor of a mobile robot will react slower to changes in the distance than a laser scanner. The time shifts can be estimated, e.g., by using the Skorokhod distance [20]. However, the delay of the sonar measurement depends on the distance measured, i.e., the time delay is not constant.

We therefore distinguish between the time \( t_x \), when the CPS variable actually adopted the value, the timestamp of the measurement \( t_s \) included in the itom (typically the time when the message has been generated and provided by the sensor) and the time the itom is received \( t_r \) or used \( t_{\text{cur}} \) (here: by the monitor), depicted in Figure 6. Unfortunately, \( t_x \) is unknown and typically does not match \( t_s \) (though often the difference is neglectable). CPS variables are often sampled periodically. The sampling period \( T \), i.e., the time between two consecutive itoms of a signal, should be small enough to follow the dynamics of the CPS variable under observation.

![Fig. 6: Timeline of an itom \( v(t_s) \).](image)

Note that the timeline or the order of these timestamps are applicable in most CPSs, regardless of the type or implementation of the communication (e.g., synchronous or asynchronous). However, the results of the computation using the itom might get distorted, especially when \( t_s \gg t_x \) (late time-stamping, e.g., due to insufficient sensor capabilities) or \( T < (t_r - t_s) \) (high communication latency, e.g., due to monitoring in the cloud).

For the above reasons, the monitor should not simply compare the last values received but consider the time delay (from \( t_x \) to \( t_{\text{cur}} \)). Still the itom is the best (latest) the monitor can make use of (without much more effort like forward estimation). An itom is therefore considered valid for a time interval or time span (and not only at the given timestamp \( t_s \) of the itom).

\[
    v(t_s) = (v, t_s) \quad v = [v, \bar{v}] \quad t = [t, \bar{t}] \quad t_s \in [t, \bar{t}] \tag{6}
\]

An itom is typically late (e.g., acquired by a sensor), but it may be valid/useful into the future, i.e., the sampling time \( t_s \) lies within the time span \( t \).

A variable \( v \) is provided at time \( t_{\text{cur}} \) when at least one corresponding itom \( v(t) \) exists with \( t_{\text{cur}} \in t \).

**Case Study:** The confidence into the value of the itom \( v \) shall express the variance of the sensor providing the observations. It should not be selected too big (masking all faults), but should cover the noise of the sensor. For instance, an interval of size \( \pm \sigma \) for a normally distributed signal captures about 68% of the sample space around the mean. Note, that also the interval of the signal to compare to, increases the accepted sample space. Outliers can be masked by a moving median filter applied on the output of the runtime monitor.

We set \( t = [t_s - \Delta, t_s] \) given the timestamp of the observation \( t_s \) and a delay \( \Delta \) which sums up the latencies caused by the sampling process, pre-processing (e.g., filtering) and communication. The size of the interval may match the sampling period \( T \) of the signal to continuously have comparable values. Note, that a sensor should be able to follow the dynamics of the system (\( T \) is small enough). Figure 7 visualizes two signals of the same variable and the confidence intervals of the latest itoms received by the monitor. For a one-dimensional itom the confidence region is a rectangle.

![Fig. 7: Two one-dimensional signals (itoms over time). The confidence regions of the latest itoms are highlighted.](image)

The demonstration in Section VI uses the specifications from sensors’ datasheets. For instance, we set the maximum delay \( \Delta_{\text{sonar}} \) of the itoms provided by the array of eight sonar sensors to \( 8 \cdot 10\text{ms} \), considering the maximum range of 3m, the sonar speed of 343m/s and an average communication delay of 1ms.
C. Comparison

Exceeding the threshold for an error is implicitly defined by the size of the intervals (in time and space). Overlapping confidence intervals indicate the itoms to be equal (Fig. 7), non-overlapping means the itoms diverge. It is a relative fast way to compare itoms (cf. itoms represented by a probability distribution), and therefore suitable for real-time systems.

The monitor is periodically \((T_m)\) fed with the latest itoms. It may save previous itoms to compensate for late receptions, so a newly received, but delayed itom \((t \ll t_r < t_{cur})\) can be compared to a past itom with similar time interval.

The total set of buffered itoms \(I\) is used as inputs to the substitutions \(S(v)\) to generate comparable (output) itoms. Two or more itoms are comparable when the itoms have a common corresponding variable and their time intervals overlap.

A monitor step consists of the following sub-steps:

- **Collect combinations** of input itoms \((v, t)\) per substitution \(s \in S(v)\) such that their time intervals overlap and a combination \(c\) contains exactly one itom per input signal \(v \in I_s\) of \(s\) (Cartesian product).

\[
\forall s \in S(v), v_1, \ldots, v_m \in I_s:\nC_s = \{(v, t_1), \ldots, (v, t_m) \mid \cap_{i=1} v_i \neq \emptyset\}
\]

- **Execute the substitutions** to generate output itoms to compare against. The value interval of the input itoms \(c \in C_s\) of a substitution \(s\) are passed through the functions of \(s\) giving the value interval of the output itom (see interval arithmetic [15]). The time interval of the output itom is the intersection of the time intervals of the inputs.

\[
\forall s \in S(v), \forall c \in C_s:\nO = \{(s, (v, t)) \mid v = f_s(c), t = \bigcap_{v_i \in c} t_i\}
\]

- **Pairwise compare** the output itoms \(O\) to calculate an error matrix of the value intervals.

\[
\forall (s, (v, t))_i, (s, (v, t))_j \in O, i \neq j:\ne
\]

- **Rank the error** to return the substitution with the highest error. The errors per substitution are summed up (sum of columns or rows of the error matrix). When an error per substitution is greater than 0 the monitor returns the failed substitution.

**Case Study:** The implementation uses pyinterval ² to pass itoms through a substitution or to identify the pairs of itoms to compare. The monitor collects itoms from step to step. In every step the list of occurred itoms is put into a queue of size \(n_{buf}\), i.e., the itoms received in the last period of \(n_{buf}\) are buffered. However, the monitor may increase the size of the buffer according to the observed delays \((t_r - t_s)\).

VI. EXPERIMENTS

In this section we demonstrate and test the fault detection. The resources to the experiments can be found on GitHub ³.

A. Setup

The demo uses the mobile robot described in Sec. III. The hosts on the rover (connected via WiFi to the notebook) only run the sensor drivers, while the controllers and the monitor are executed on the notebook (Intel i7 2.1GHz x 4, 8GB RAM, Ubuntu, ROS and its nodes run in Docker containers).

The rover is tele-operated via the notebook towards a wall (Fig. 8). The ROS messages of the sensors (monitored inputs) and the monitor itself (failed substitution and additional debug output) are logged.

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²https://pypi.org/project/pyinterval/

³https://github.com/tuw-cpsg/paper-shsa-monitor-experiments
observations received and compare these against each other. At time 5.5s this would lead to a false positive, because the distance captured by the ToF camera at time 5s is already outdated. However, our monitor considers the different sample rates and only compares values where the time intervals overlap. Note that transient faults (outliers) can be mitigated by an optional moving-median or moving-average filter of the monitor output.

C. Fault Detection

To test other scenarios of timings (timestamp vs. reception of an observation) and faults (in space and time), we inject typical faults to a generated set of itoms. The generated itoms per monitor step have equal value and slightly shifted timestamps. To reliably identify a fault in our setup, we provide three substitutions where each substitution uses a different itom (diverse substitutions) and assume only one simultaneous fault in the value domain of the inputs.

Table III summarizes the types of faults and how these are injected. All faults are injected for a specific period of time \([t_{\text{start}}, t_{\text{end}}]\). The buffer size \(n_{\text{buf}}\) of the monitor is set to one for testing faults in the value domain.

Figures 12 and 13 visualizes fault detection of 3 substitution outputs. The top plot annotates the time span with a description of the injected fault. The height of the bar references the substitution index to which the fault has been injected. The generated value is represented by a marker while the uncertainty (intervals) is plotted as two error bars along the x-(time) and y-axis (value). The upper plot presents the timeline of reception of the monitor inputs \((t_r)\) of the itoms). The lower plot shows the outputs of the substitution executed by the monitor, i.e., the itoms at the time of occurrence \((t_s)\) or \(t\) of the itoms). The bottom indicates the substitution index with the highest error.

For instance, in Fig. 12 stuck-at 0 and random noise has been applied to the input of substitution \(s_1\) and \(s_0\), respectively. The monitor gathers the itoms since the last call (here within the last second) and compares the outputs of the substitutions when the time intervals overlap. Because the value intervals of \(s_1\) during the time marked with “stuck-at 0” do not overlap the value intervals of the other substitutions \(s_1\) has an error \(\neq 0\) and the monitor indicates the failed substitution as \(s_1\).

In Fig. 13 the capability to compensate delays is tested. The input of \(s_1\) is missing in the monitor call at time 3s. The faulty substitution is miss-classified because of only two available outputs to compare (no majority vote possible). However, with a buffer size of \(n_{\text{buf}} = 2\) the fault can be detected (the monitor
We present a monitor querying the knowledge base to find redundancies and which can detect faults of observation components by comparison. The knowledge base has been encoded in Prolog implemented with the ProbLog library which enables the user to change the knowledge base during runtime, and add or remove information about the availability of observations. The monitor can therefore master technological or functional changes in the CPS. Moreover, we presented an observation model considering uncertainties in space and time (e.g., noise or delays) of observations collected by the monitor.

In ongoing and future work we want to investigate other methods to compare and rank the redundant observations over time. Furthermore, we look into how the redundancy shall be selected (diversity) or proper fault diagnosis can be applied.

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