Fault detection combining adaptive degrees of freedom χ²-statistics and interval approach for nonlinear systems
Quoc Hung Lu, Soheib Fergani, Carine Jauberthie

To cite this version:
Quoc Hung Lu, Soheib Fergani, Carine Jauberthie. Fault detection combining adaptive degrees of freedom χ²-statistics and interval approach for nonlinear systems. The 22nd World Congress of the International Federation of Automatic Control (IFAC), Jul 2023, Yokohama, Japan. hal-04069589

HAL Id: hal-04069589
https://laas.hal.science/hal-04069589
Submitted on 8 Jun 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Fault detection combining adaptive degrees of freedom $\chi^2$-statistics and interval approach for nonlinear systems

Quoc Hung Lu* Soheib Fergani* Carine Jauberthie*

* LAAS-CNRS, 7 avenue du Colonel Roche, 31400 Toulouse, France (e-mail: qhlu@laas.fr, sfergani@laas.fr, cjauber@laas.fr).

Abstract: An enlargement of the Adaptive degrees of freedom $\chi^2$-statistics (ADFC) method to fault detection for nonlinear systems with mixed uncertainties (stochastic and bounded uncertainties) is presented in this paper. The ADFC approach, primarily developed for fault detection in case of linear systems, is then combined with the Reinforced likelihood box particle filter (RLBPF). A residual generator is used, followed by the adaptive amplifier coefficient (a.a.c.) concept in the decision making stage. Then, the proposed approach is applied to a nonlinear Magneto-Rheological damper model to illustrate the efficiency of the method.

Keywords: Adaptive Innovation-based method, Fault diagnosis, Adaptive amplifier coefficient, Automotive quarter model.

1. INTRODUCTION

In modern control system, many important issues are required to be solved such as the availability, cost efficiency, reliability, operating safety, environmental protection,... Therefore, fault diagnosis becomes indispensable and one of the main solutions for these requirements. A fault must be diagnosed as early as possible, even if it may be tolerable, to prevent any serious consequence. The fault diagnosis consists in three tasks: fault detection (FD), fault isolation and fault estimation (or fault identification), in which FD is the first stage and building block of any further task. For all the above reasons, this paper is focusing on the development of a reliable FD strategy.

Model-based FD approach applied to dynamical systems using analytical redundancy is widely used. It consists in two stages: residual generation and residual evaluation or decision making. The residual is normally a difference between a measured signal and an estimate of the later. It should be zero-valued in the fault-free case and diverge from zero in the faulty case. In the second stage, the residual (or its transformation via a function) is compared to a constant threshold or an adaptive threshold depending on the fault detection method. Especially, using observer-based concept, a filter or an observer is the core of the residual generator which provides the estimate quantity of interest to deduce the residual. This is the structure of the FD method proposed in the paper (Fig.1). The most advantage of this structure is that it can easily combine filter/observer and decision making method (pre-existent or to be developed) for adapting to various contexts and purposes.

The challenge of the present work is twofold: the non-linearity of the system and the mixed uncertainties context (bounded and stochastic uncertainties). Indeed, in the literature, most of researches about FD are devoted to linear system while fewer articles provide solution for non-linear counterpart. Nonlinear systems are usually assumed to be smooth “enough” with mild conditions for a nice linearization, then techniques for the linear case can be applied. For instance, the Standard Kalman Filter (SKF) (Kalman, 1960) and its extensions (included Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Robust Kalman filtering, Interval Kalman Filter (IKF), Minimum Upper Bound of Variance Interval Kalman Filter (UBIKF), Optimal upper bounded Interval Kalman Filter (OUBIKF)) have been applied in residual generators of different FD schemes/methods. We refer to Zhong et al. (2018) which provides a survey on model-based fault diagnosis for linear discrete time-varying (LTV) systems with useful references concerning FD using SKF, EKF and UKF. Otherwise, Xiong et al. (2013) proposed FD method using IKF, Tran (2017) with FD using UBIKF, Lu et al. (2021) with FD based on OUBIKF, while output observer (non interval case) for FD in linear systems can be found in Mohamadi et al. (2016). Furthermore, also for linear system, set-membership methods in fault diagnosis are concerned in Puig (2010) while interval observer approach for FD is investigated, for instance, in Raka and Combastel (2013); Chevet et al. (2021). Some of these works (Xiong et al. 2013; Tran 2017; Lu et al. 2021) deal with mixed un-
In the present paper, an enlargement of the Adaptive degrees of freedom \( \chi^2 \)-statistics (ADFC) method (Lu et al. 2022) to FD for nonlinear systems is proposed. The method combines the Reinforced likelihood box particle filter (RLBPF) developed in Lu et al. (2022) (versus OUBKF for linear systems) together with the adaptive amplifier coefficient (a.a.c.) concept in the decision making stage. In doing so, the twofold challenge of the issue is met.

Interval analysis is a primary tool for computation of the method, no strict condition is required for (non linear) dynamic functions of the system.

The paper is organized as follows. Preliminaries are provided in Section 2, including used notations and essential of interval analysis. Section 3 presents main results with the extended FD method. Simulations based on the nonlinear Magneto-Rheological damper model are provided in Section 4. Finally, Section 5 provides conclusions and perspectives.

2. PRELIMINARY

2.1 Essential of interval analysis

A real interval \( [x] = [\underline{x}, \overline{x}]: = \{ t \in \mathbb{R} | \underline{x} \leq t \leq \overline{x} \} \) is a closed connected subset of \( \mathbb{R} \) and characterized by two extreme values \( \underline{x} \leq \overline{x} \). A real interval matrix \( [X] = ([x_{ij}]) \) of dimension \( p \times q \) also called an interval in \( \mathbb{R}^{p \times q} \), is a matrix with real interval components \( [x_{ij}], i \in \{1,...,p\}, j \in \{1,...,q\} \). Write \( X \in [X] \) to indicate a point matrix \( X = (x_{ij}) \) belonging element-wise to \( [X] \). Define:

- \( \sup([X]) \triangleq \sup([x_{ij}]) \equiv \overline{X} \),
- \( \inf([X]) \triangleq \inf([x_{ij}]) \equiv \underline{X} \),
- \( \text{mid}([X]) \triangleq ([X] + \underline{X})/2 \),
- \( \text{rad}([X]) \equiv ([X] - \underline{X})/2 \),
- \( \text{width}([X]) \triangleq \overline{X} - \underline{X} \),

which are called respectively (resp.) the largest matrix, the smallest matrix, the midpoint matrix, the radius matrix and the width matrix of \( [X] \). Define the hull of a closed set \( S \) and the hull of two interval matrices \( [X_1], [X_2] \) of the same dimension as follows: hull(\( \emptyset \)) \( \triangleq \emptyset \), hull(\( S \)) \( \triangleq \inf(S), \sup(S) \) and hull(\( [X_1], [X_2] \)) \( \triangleq \text{inf}([X_1], [X_2], \text{sup}([X_1], [X_2])) \). We also write an interval as: \( [X] = \langle [\underline{X}, \overline{X}] \rangle = \text{mid}([X]) \pm \text{rad}([X]) \).

Basic interval operators \( \circ \in \{+, -, \times, \div, \} \) defined in Jaulin et al. (2001) can be used to compute directly all operations \( [u] \circ [v] \) and \( \alpha \circ [u] \), for real intervals \([u], [v] \) and \( \alpha \in \mathbb{R} \), without any further approximation algorithm. Then, interval matrix computations are defined similarly to matrix computations using the basic operators while more general operators are constructed by means of inclusion function \( [f] \) defined in Definition 1 below. In practice, the package Intlab (Rump 1999) developed for Matlab (also existing in Octave and C/C++) is used for computations.

Definition 1. Let \( f \) be any function from \( D \subseteq \mathbb{R}^m \) to \( \mathbb{R}^n \). An inclusion function of \( f \) is a function \([f]\) that maps any interval \([x]\) in \( D \) to an interval \([f([x])] \) in \( \mathbb{R}^n \) containing the image set \( f([x]) \). Symbolically, \([f] : [x] \mapsto [f([x])] \supset f([x]), \forall [x] \subset D\), with \([f]([x])\) is an interval in \( \mathbb{R}^n \). The minimal inclusion function of \( f \) is a function \([f]^\circ\) so that for every \([x] \subset D\), \([f]^\circ([x])\) is the smallest interval containing \( f([x]) \).

2.2 Other notations

A positive semidefinite matrix \( X \) is denoted by \( X \succeq 0 \). Let \( M, N \in \mathbb{R}^{n \times n} \), define \( N \preceq M \) if \( M - N \succeq 0 \), \( M \succeq 0 \), \( M \preceq 0 \) and \( M \succeq N \). Let \( \emptyset \not\subseteq \Omega \subset \mathbb{R}^{n \times n} \), \( M \) is an upper bound (resp. lower bound) of \( \Omega \), denoted \( \Omega \preceq M \) (resp. \( M \preceq \Omega \)), if \( X \preceq M \) (resp. \( M \preceq X \)), \forall X \in \Omega \.

Denote also: \( S_t([X]) \triangleq \{X \in [X] : X = X^T \text{ and } X \succeq 0\} \), \( \mathbb{E}(x) = 1 \) if the conditions \( x \) are true and \( \mathbb{E}(X) = 0 \) otherwise, \( \text{mean}(x) = \sum_{i=1}^{n} x_i/n \), \forall x \in \mathbb{R}^n \). The notation \( p : l \) \( (p \preceq q) \) is used for a range from \( p \) to \( q \) with step \( l \). For \( l = 1 \), we write \( p : q \). A sequence of variables can be noted interchangeably as \( w_1,...,w_q \) or \( w_1 : w_q \).

3. MAIN RESULTS

3.1 Model and problem formulation

Consider the following system (1) with additive measurement noises:

\[
\begin{align*}
\Sigma : \quad \begin{cases}
x_k = f_k(x_{k-1}, u_k, w_k), \\
y_k = h_k(x_k, u_k) + v_k + f_k',
\end{cases} \quad k \in \mathbb{N}^*,
\end{align*}
\]

where \( x_k \in \mathbb{R}^{n_x} \) and \( y_k \in \mathbb{R}^{n_y} \) represent state variables and measures respectively, \( u_k \in \mathbb{R}^{n_u} \) inputs, \( w_k \in \mathbb{R}^{n_w} \) state disturbances/noises, \( v_k \in \mathbb{R}^{n_y} \) measurement noises, \( f_k' \in \mathbb{R}^{n_y} \) additive sensor fault vectors. Each of its components corresponds to a sensor fault. Thus, the fault vector \( f_k' \) can be of the multiple or single error type.

Assumptions (A)

(A1) Given \([x_0], [u_k], [w_k], [y_k], [\mu_k], f_k, h_k, k \in \mathbb{N}^*\).

(A2) \( v_k \sim \mathcal{N}(\mu_k, \Sigma_k) \) with unknown \( \mu_k \) and \( \Sigma_k \).

(A3) \( x_k \in [x_0], \quad u_k \in [u_k], \quad w_k \in [w_k], \quad y_k \in [y_k], \quad \mu_k \in [\mu_k] \) and \( \Sigma_k \in \Sigma_k \).

(A4) \( \Sigma_k \) is unknown.

Remark 2. The measurements are given as intervals \([y_k]\) due to the sensor precision. In many theoretical problems and applications, it is assumed that \( \mu_k \equiv [\mu_k] \equiv 0 \) for simplicity. It is natural that \( \Sigma_k \) is unknown and the mention of this fact is necessary for the subsequent development. Assumptions (A3) are implicitly deduced that the belonging of unknown real (true) terms in their corresponding intervals are certain. This certainty can be understood as “with probability 1”. System (1) with
assumptions (A) can be adapted to a wide range of applications. The system is time varying, the uncertainties come from system disturbances or measurement noises with different kinds (stochastic/bounded uncertainties).

To evaluate the fault detection performance, four indicators are introduced. Assume that system (1) is applied for $N$ iterations among which faults occur in a time interval $\mathcal{R}$ with length $l$ ($0 \leq l \leq N$). Actually, $\mathcal{R}$ may be an interval or union of intervals but is called hereafter an error range for simplicity. Then, a detection signal is denoted by $\pi_k$ which has values in $\{0; 1\}$. A signal $\pi_k = 1$ is called a right detected signal if $k \in \mathcal{R}$ and a false detected signal if $k \notin \mathcal{R}$. Then, the four indicators are defined as follows:

+ **Detection Rate**: $\text{DR} = \sum_{k \in \mathcal{R}} \frac{|\pi_k = 1|}{N} \times 100\%$

+ **False Alarm Rate**: $\text{FAR} = \sum_{k \notin \mathcal{R}} \frac{|\pi_k = 1|}{N} \times 100\%$

+ **Efficiency**: $\text{EFF} = \text{DR} - \text{FAR}$

+ **No detection rate**: $\text{NDR} = 100\% - \text{DR}$

3.2 Adaptive approach combining RLBPF to fault detection

In this section, the ADFC method is extended to a more general framework, including nonlinear dynamical systems. This approach has also the ability to combine with several set-membership estimation filters (w.r.t. some conditions in see Theorem 3). In the following, the proposed approach is applied with RLBPF and the extension is based on Theorem 3.

**Theorem 3.** Consider system (2) with assumptions (A) and fault free case ($f_k^x = 0, \forall k \in \mathcal{N}^+$.)

Let $r_k = y_k - h_k(x_k, u_k) - \mu_k$ be the residual, $[\tilde{x}_k]\}$ be interval estimates of an interval filter and  

$$[\tilde{x}_{k+1}] = [f_k + 1][\tilde{x}_k], [u_k + 1], [w_{k+1}], \\text{and} \\tilde{[y]}_{k+1} = [y_k] - [h_k + 1][\tilde{x}_{k+k}], [u_k + 1] - [\mu_k].$$

Then, for all $k \geq 1$:

(a) $y_k = x_k \sim N(m_k, \Sigma_k)$ where $m_k = h_k(x_k, u_k) + \mu_k$ and the notation $y_k|x_k$ means for the stochastic variables $y_k$ given (or knowing) $x_k$. When $v_k$ is a bounded disturbance, then $x_k$ is deterministic and $y_k|x_k = y_k$.

(b) $r_k \sim N(0, \Sigma_k)$ where $\Sigma_k \in \mathcal{S}_k$.

Consequently, a confidence interval of (more than) 99.7% of all admissible $r_k$ can be deduced as

$$\text{Cl}(r_k) = \pm 3\sqrt{\text{diag}([\Sigma])},$$

with $	ext{diag}(A) = (a_{11}, ..., a_{nn})^T, \forall A = (a_{ij}) \in \mathbb{R}^{n \times n}$.

Assuming further that $x_k \in [\tilde{x}_{k+k}]$ at every $k \geq 1$, then:

(c) $x_{k+1} \in [\tilde{x}_{k+1+k}]$ with certainty (probability 1),

(d) $r_{k+1} \in [\tilde{r}_{k+1}]$ with certainty (probability 1).

**Proof.** Knowing $x_k$ in either cases of $w_k$ (disturbance or stochastic noise), the term $h_k(x_k, u_k)$ is known (or deterministic). So, since $v_k \sim N(\mu_k, \Sigma_k)$ then $y_k|x_k = h_k(x_k, u_k) + v_k$ is normally distributed with mean $m_k = h_k(x_k, u_k) + \mu_k$ and covariance $\Sigma_k$. Also, by the property of normal distribution, it concludes that $r_k \sim N(0, \Sigma_k)$. So, statements (a) and (b) are proved.

To prove the statements (c) and (d), the inclusion function property is used, that is: $f(x) \in \{f(x)\}_x \forall x \in [x]$ with certainty. By assumptions (A3) and $x_k \in [\tilde{x}_{k+k}]$, then

- $f_{k+1}(x_k, u_k, w_{k+1}) = x_{k+1} \in [\tilde{x}_{k+1+k}],$
- $h_{k+1}(x_{k+1}, u_{k+1}) \in [h_{k+1}][\tilde{x}_{k+1+k}}, [w_{k+1}],$
- $\mu_{k+1} \in [\mu_{k+1}]$ with certainty. Thus, it implies that $r_{k+1} \in [\tilde{r}_{k+1}]$ with certainty ensured by the inclusion function property.

**Remark 4.** The notation $[\tilde{x}_{k+k}]$, $k \geq 1$, denotes an interval estimate provided by the corresponding interval filter at the end of the time instant $k$. $[\tilde{x}_{k+k}]$ denotes the propagation box at the next iteration that allows to obtain $[\tilde{x}_{k+1+k}]$.

**Remark 5.** The assumption $x_k \in [\tilde{x}_{k+k}]$ at every $k \geq 1$ is strong and related to the performance and convergence of the filter. Practically, an interval filter that has the $O(\%) = \sum_{k=1}^{N} \frac{1}{N+1} x_k \in [\tilde{x}_{k+k}] \times N \times 100\%$ measuring the percentage of $x_k \in [\tilde{x}_{k+k}]$ greater than some level (e.g. 80% or 90%) can be suited to the PD procedure of the ADFC method, although it may cause certain false alarms.

**Principle of the method**

Since $r_k \sim N(0, \Sigma_k)$ then $\xi_k \sim r_k N_{k-1}^{-1} r_k$ is $\chi^2$-distributed with $n_y$ degrees of freedom (d.f.) $(\xi_k \sim \chi^2(n_y))$. Thus, for any $a_k > 0$ so that $S_\kappa(\Sigma_k) \leq a_k I_{n_y}$,

$$\xi_k \geq r_k^T a_k r_k = r_k^T a_k r_k / a_k \equiv \xi_k.$$

However, $r_k$ is unknown and $r_k \in [\tilde{r}_k]$ with a computable $[\tilde{r}_k]$. So, we aim at using the statistic

$$U_k = \{\text{sup}(\{[\tilde{r}_k]^T [\tilde{r}_k] / a_k\})\} = \{\text{sup}(\{[\tilde{r}_k]\})\},$$

as proposed in [1, 2021] with the $a_k$ aforementioned. The statistic $U_k$ is approximated by a $\chi^2$-distributed random variable with an appropriate d.f. $k = n_y$ by determining $a_k$ and using an a.a.c. $\kappa$.

**Explanation.**

Theoretically, for ensuring $S_\kappa(\Sigma_k) \leq a_k I_{n_y}$, it is required that maximum $\{\text{diag}(\Sigma_k)\} < a_k I_{n_y}$ [1, 2019]. The more $a_k$ is large, the more $\xi_k$ is small and vice versa. Besides, note that $r_k \in [\tilde{r}_k]$ is with probability 1 (Theorem 3), where $r_k \sim N(0, \Sigma_k)$, $\Sigma_k \in \mathcal{S}_k$. This implies $[\tilde{r}_k] \supseteq \text{Cl}(r_k)$ and $[\tilde{r}_k]$ must be greater considerably than the confidence interval in order to contain $r_k$ with such a certainty. Therefore, an appropriate (optimal) $a_k$ must ensure a compromise between $[\tilde{r}_k]$ and $\text{Cl}(r_k)$, says a function of $[\tilde{r}_k]$ and $[\Sigma_k]$, provided that:

$$\max\{\text{diag}(\Sigma_k)\} < a_k \equiv \phi_k([\tilde{r}_k], [\Sigma_k]) < \max\{r_k\}.$$

In the development of this section, a simple proposition for $a_k$ is that

$$a_k = \lambda_1 \cdot \text{mean}(\text{width}(\tilde{r}_k))$$

so that $S_\kappa(\Sigma_k) \leq a_k I$, (4) where $\lambda_1 > 0$ is a scaling factor changing depending on the considered application.

The a.a.c. $\kappa$ is involved with the threshold $\delta_k$ to which $U_k$ is compared: $P(\chi^2(k \times n_y) \geq \delta_k) = \alpha$, where $\alpha$ is a given significant level. So, $U_k \approx \chi^2(k \times n_y) \leq \delta_k$ with confidence level $1 - \alpha$ in the fault free case. $\kappa$ is chosen [1, 2021] as

$$\kappa_k = \text{mean}(\text{width}(\tilde{r}_k)).$$
so that it is sensitive to the fault, large enough to obtain a small FAR (e.g., ≤ 5%) in the fault free case, sensitively affected by width([\hat{r}_k]) as well as \( U_k \) but it does not increase as fast as the later whenever a fault occurs and affects on the width([\hat{r}_k])). This choice also provided a good performance fault detection with FAR < 3% in several scenarios of simulations presented in the referenced paper.

Thus, in the present work, it is raised naturally that
\[
r_k = \lambda_2 \cdot \text{mean}\{\text{width}([\hat{r}_k])\}
\]  

(6)
is chosen for adapting to different applications and purposes by using different level parameters \( \lambda_2 > 0 \).

Thanks to the use of RLBPF with interval analysis properties, the enlarged method is provided without assumptions about dynamic functions \( f_k \) and \( h_k \) nor any linearization is required.

Remark 6. In linear systems, residuals are determined by \( r_k = y_k - h_k(x_k, u_k) - \mu_k \) where \( \hat{x}_k \) is an estimate of \( x_k \) and \( h_k \) is a linear function. Thus, \( r_k \) can be computed explicitly at every time step as well as its distribution under the SKF assumptions. Consequently, with additional bounded uncertainties, the covariance of \( [r_k] \) is well determined as some computable matrix \( [\Sigma_k] \) and \( a_k \) has a more accurate choice using Theorem 2 in [Lu et al. (2021)] so that \( [\Sigma_k] \preceq a_k I_{2\times2} \). Evidently, if \( [\Sigma_k] \) is assumed to be known in assumption (A4), \( a_k \) can be computed in the same manner. In this work, we consider \( r_k = y_k - h_k(x_k, u_k) - \mu_k \), although it is unknown, and compute \([\hat{r}_k]\) ensuring that \( r_k \in [\hat{r}_k] \) with certainty.

The ADFC method is eventually enlarged to a more general framework of non linear system, as presented above. It can be summarized by the following algorithm.

Algorithm 1 ADFC method to nonlinear system

1: Initialization: \( \alpha, \lambda_1, \lambda_2, [\hat{x}_{0|0}] \equiv [x_0], f_k, h_k, [u_k], [\mu_k], [\Sigma_k], k = 1, 2, ..., N. 
2: for \( k = 1, 2, 3, ... N \) do
3: Use RLBPF to get: \([\hat{x}_{k|k-1}] = [\hat{x}_{k|k-1}|\lambda_1, [\hat{x}_{k|k-1}], [\hat{r}_k],[\hat{u}_k])\]
4: \([\hat{r}_k] = [y_k] - [h_k][\hat{x}_{k|k-1}], [\hat{r}_k] - [\mu_k]\]
5: \( a_k = \lambda_1 \cdot \text{mean}\{\text{width}([\hat{r}_k])\}\)
6: \( U_k = \sup\{\text{abs}\{[\hat{r}_k]^T[\hat{r}_k]/a_k\}\}\)
7: \( k_k = \lambda_2 \cdot \text{mean}\{\text{width}([\hat{r}_k])\}\)
8: Find \( \delta_k \) s.t.: \( \mathbb{P}(\chi^2(k_k, \alpha) > \delta_k) = \alpha \).
9: Detection signal : \( \pi_k = \|U_k > \delta_k\).
10: end for

4. APPLICATION

4.1 Quarter vehicle model

The vertical quarter car model is often used to study the vertical behavior of a vehicle according to the suspension characteristic (passive or controlled) (Fig. 2). When controlled suspension is considered, the passive damper \( F_c \) is removed and replaced by an actuator that provides a force \( u \) either active or semi-active depending on the chosen actuator (Fig. 3). In figures 2, the sprung mass \( m_s \) and unsprung mass \( m_{us} \) represent respectively the vehicle chassis and the vehicle wheel. \( z_s \) and \( z_{us} \) are respectively the relative vertical displacement of the vehicle chassis and the vehicle wheel with respect to the road. \( z_r \) is considered as the road disturbance.

![Fig. 2. Quarter vehicle model](image)

![Fig. 3. Quarter vehical model - Passive (left) and Active control (right) modes](image)
4.2 Simulation

Consider the following nonlinear system modeling the MR (Magneto-Rheological) damper:

\[
\begin{align*}
\dot{m}_s \dot{z}_s &= -k_s z_{def} - F_{\text{damper}} \\
\dot{m}_u \dot{z}_{us} &= k_s z_{def} + F_{\text{damper}} - k_t (z_{us} - z_r) ,
\end{align*}
\]

(9)

\[ F_{\text{damper}} = c_0 \dot{z}_{def} + k_0 \dot{z}_{def} + f_f \tanh (c_1 \dot{z}_{def} + k_1 \dot{z}_{def}) , \]

where \( c_0, k_0, c_1, k_1 \) are constant chosen according to Fergani-Juarez et al. (2008) such that \( c_0 = 1500 \) (Nsm\(^{-1}\)), \( c_1 = 129 \) (sm\(^{-1}\)), \( k_0 = 989 \) (Nm\(^{-1}\)), \( k_1 = 85 \) (m\(^{-1}\)), and \( f_f \) is a controllable force depending on the input current \( I \) and satisfying the dissipativity constraint

\[ 0 < f_{\text{min}} \leq f_I \leq f_{\text{max}} . \]

In this simulation, we consider \( f_{\text{min}} = 1000 \) N/m and \( f_{\text{max}} = 1500 \) N/m. Other parameter values used in the simulation are presented in Table 1 issued from Fergani-Juarez et al. (2014).

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Unit</th>
<th>Signification</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_s )</td>
<td>315</td>
<td>kg</td>
<td>sprung mass</td>
</tr>
<tr>
<td>( m_u )</td>
<td>37.5</td>
<td>kg</td>
<td>unsprung mass</td>
</tr>
<tr>
<td>( k_s )</td>
<td>29500</td>
<td>N/m</td>
<td>suspension linearized stiffness</td>
</tr>
<tr>
<td>( k_t )</td>
<td>208000</td>
<td>N/m</td>
<td>tire stiffness</td>
</tr>
<tr>
<td>( z_{def} )</td>
<td>([-0.09:0.05])</td>
<td>m</td>
<td>suspension bound (stroke limit)</td>
</tr>
</tbody>
</table>

The system (10) will be discretized using the Fourth order Runge-Kutta method (Kincaid and Cheney, 1991) with a chosen sampling time \( T = 10^{-3} \) (s). The resulted discrete time state dynamical system is denoted by:

\[ x_k = f(x_{k-1}, u_k, w_k) + \eta_k, \quad k \in \mathbb{N}^* , \]

(11)

where \( \eta_k \) is assumed to be Gaussian noise with zero mean and covariances \( 10^{-3} I_{n_x} \). The corresponding observed measurements are assumed to be \( z_{def} \) at every time step, thus the measurement dynamical equation can be expressed in the form

\[ y_k = h(x_k) + v_k = C x_k + v_k , \quad C = [1, 0, -1, 0] \]

where \( v_k \) is assumed to be Gaussian with mean \( \mu_k \in [\mu_k] = [-0.005, 0.005] \) and variance \( \sigma_k^2 \in [\sigma_k^2] = [1, 4] \times 10^{-6} \). The precision of the sensors is assumed to be \( \pm 0.005 \) (m).

State and measurement simulation: Assume that the initial state is \( x_0 = (0, 0, 0, 0)^T \), the control force input is set to get its maximum value constantly \( u = 1500 \) for all time instants and the road disturbance is set as \( w = 0.05 \max (0, \sin(\pi t)) \). \( \{x_k, y_k\}_{k=1:N} \) are then generated using (11) and (12) for \( N = 5000 \) steps. The measurements obtained will be intervals \([y_k] = y_k \pm 0.005 \) because of sensor errors.

For the fault detection purpose, a fault of an amplitude of \( b = 0.02 \) m is added to the simulated observed measurements in a range \( R \) with length \( l = 200 \) and the following choices are used: \( \lambda_1 = 0.02, \lambda_2 = 10, \alpha = 0.03 \).

A simulation result is figured out in Figures 4 - 6. In the error range, the residual deviate from 0 (Fig. 4) and most of the statistics \( U_k \) (blue line) passe over the adaptive thresholds \( \delta_k \) (red line) (Fig. 5).

Comparing to the general system (8), in the MR damper model (9), assume that \( F_{dz} = 0 \) and \( F_{lz} = k_t(z_{us} - z_r) \).

Putting

- \( x = [z_s, \dot{z}_s, z_{us}, \dot{z}_{us}]^T \) as state variable under consideration and \( x(t), i \in \{1, ..., 4\} \), are its components,
- \( u = f_I \) as controllable input,
- \( w = z_r \),

then \( x, u, w \) are functions of time \( t \) and the state-space representation of (9) is expressed in the form

\[
\dot{x}_t = f(t, x_t) = \begin{bmatrix} f_1(t, x_t) \\ f_2(t, x_t) \\ f_3(t, x_t) \\ f_4(t, x_t) \end{bmatrix} ,
\]

(10)

where

\[
\begin{align*}
f_1(t, x_t) &= e_2^T x_t , \\
f_2(t, x_t) &= e_4^T x_t , \\
f_3(t, x_t) &= (a^T x_t - u_t \tanh(b^T x_t)) / m_s , \\
f_4(t, x_t) &= (c^T x_t + u_t \tanh(b^T x_t) + k_3 w_t) / m_{us} ,
\end{align*}
\]

with \( e_i \)’s are \( i \)-th column vectors of the corresponding identity matrix and

\[
a = \begin{bmatrix} -k_s & -k_0 \\ k_s & k_0 \\ -c_0 \\ c_0 \end{bmatrix} , \quad b = \begin{bmatrix} k_1 \\ -c_1 \end{bmatrix} , \quad c = \begin{bmatrix} k_s + k_0 \\ -k_s - k_0 - k_t \\ -c_0 \end{bmatrix} .
\]
Then the fault detection procedure is replicated for $L = 100$ times where the error range $R$ is chosen randomly and indicators DR, NDR, FAR, EFF are yielded as their corresponding means after $L$ times of simulations (Table 2). For a fault value $b = 0.02m$, the efficiency index (EFF) is about 66%.

<table>
<thead>
<tr>
<th>$b$</th>
<th>DR(%)</th>
<th>NDR(%)</th>
<th>FAR(%)</th>
<th>EFF (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.02</td>
<td>67.715</td>
<td>32.285</td>
<td>1.2762</td>
<td>66.439</td>
</tr>
</tbody>
</table>

Table 2. ADFC method - Fault detection to a Quarter vehicle model.

5. CONCLUSION AND PERSPECTIVE

An adaptive approach of sensor fault detection applied to nonlinear discrete time dynamical system is proposed. The approach combines RLBPF with a hypothesis testing method using $\chi^2$-statistics with adaptive degrees of freedom. Theoretical framework is developed thanks to interval analysis. A great flexibility of adjusting several factors (parameters) makes the approach highly fitted to multiple applications.

Simulations are performed using the nonlinear Magneto-Rheological damper model. The results show the efficiency of the proposed method providing good performances w.r.t the fault magnitudes.

The method is developed however in the framework of (additive) sensor fault systems. Extend this method to deal with other kinds of fault (e.g. actuator faults) and with fault identification is a perspective of our future research.

REFERENCES


