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A GMDH neural network-based approach to passive robust fault detection using a constraint satisfaction backward test

Vicenç Puig[a,*], Marcin Witczak[b], Fatiha Nejjari[a], Joseba Quevedo[a], Józef Korbicz[b]

[a] *Automatic Control Department (ESAII) – Campus de Terrassa, Universidad Politécnica de Cataluña (UPC), Rambla Sant Nebridi, 10. 08222 Terrassa, Spain*

[b] *Institute of Control and Computation Engineering, University of Zielona Góra, Ul. Podgórna 50, 65-246, Zielona Góra, Poland*

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Abstract

This paper proposes a new passive robust fault detection scheme using non-linear models that include parameter uncertainty. The non-linear model considered here is described by a group method of data handling (GMDH) neural network. The problem of passive robust fault detection using models including parameter uncertainty has been mainly addressed by checking if the measured behaviour is inside the region of possible behaviours based on the so-called *forward test* since it bounds the direct image of an interval function. The main contribution of this paper is to propose a new *backward test*, based on the inverse image of an interval function, that allows checking if there exists a parameter in the uncertain parameter set that is consistent with the measured system behaviour. This test is implemented using interval constraint satisfaction algorithms which can perform efficiently in deciding if the measured system state is consistent with the GMDH model and its associated uncertainty. Finally, this approach is tested on the servoactuator being a FDI benchmark in the European Project DAMADICS.

Keywords: Fault detection; Fault diagnosis; Robustness; Adaptive threshold; Neural network

1. Introduction

Model-based fault detection is based on the use of mathematical models of the monitored system. The better the model used to represent the dynamic behaviour of the system, the better will be the chance of improving the reliability and performance in detecting faults. However, modelling errors and disturbances in complex engineering systems are inevitable, and hence there is a need for developing robust fault detection algorithms. The *robustness* of a fault detection system means that it must be only sensitive to faults, even in the presence of model-reality differences (Chen and Patton, 1999; Korbicz et al., 2004). One of the approaches to the robustness problem, known as *passive*, enhances the robustness of the fault detection system at the decision-making stage, mainly using an adaptive threshold (Emami-Naeini et al., 1988; Horak, 1988). Contrary to the *active* approaches (Chen and Patton, 1999), the adaptive threshold-based passive approach does not rely on eliminating the effect of model uncertainty in the residual through the perfect decoupling of an unknown input representing model uncertainty. Indeed, the adaptive threshold-based techniques rely on propagating model uncertainty to the residual, and then bounding the resulting residual uncertainty. Of course, this approach has the drawback that faults that produce a residual deviation smaller than the residual bounds due to parameter uncertainty will not be detected. On the other hand, there are examples for which fault directions are very similar to that of an unknown input. This may lead to a situation in which the effect of some faults is minimized and hence they may be impossible to detect. This constitutes the main drawback of the active approaches such as the celebrated unknown input observer (Chen and

*Corresponding author. Tel.: +34 619 63 80 70; fax: +34 93 401 7045.
E-mail addresses: vicenc.puig@upc.edu (V. Puig), M.Witczak@issi.uz.zgora.pl (M. Witczak).

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Patton, 1999; Korbicz et al., 2004). In other words, all approaches that make use of the idea of an unknown input also inherit this unappealing characteristic.

In spite of the fact that a large spectrum of analytical techniques for fault detection and isolation (FDI) of non-linear systems can be found in the literature (see Chen and Patton, 1999; Korbicz et al., 2004 and the references therein), they all usually suffer from the lack of an appropriate mathematical description of the system being considered. If there is no, or not sufficiently accurate analytical models, then the one feasible way is to use the so-called soft computing techniques, such as neural networks (Korbicz et al., 2004; Ruano, 2005). At the beginning of the 1990s neural networks were proposed for identification and control (see e.g., Narendra and Parthasarathy, 1990; Dzieliński, 2002; Tan, 2004 and the references therein). A rapid development concerning applications of neural networks in control engineering resulted in a vast number of publications related with this subject. In 1992, Hunt et al. confirmed the fast development of this research area by publishing a survey on neural networks in control engineering. In 1995, a similar work was published by Sjoberg et al. in the context of system identification with neural networks. Nowadays, the vast number of applications has increased significantly. Fault diagnosis constitutes one of the thrusts of the research effort on neural networks for control (Patton and Korbicz, 1999; Zitek et al., 1999, Korbicz et al., 2004).

This paper focuses on the problem of passive robust fault detection using non-linear models that are designed with neural networks. Contrary to the industrial applications of neural networks that are presented in the literature (see Korbicz et al. (2004) and the references therein), the proposed approach takes into account the parameter uncertainty of a neural model when generating an adaptive threshold to obtain passive robustness. The non-linear model considered here is described by a group method of data handling (GMDH) neural network (Korbicz et al., 2004; Witczak and Mrugalski, 2003; Witczak et al., 2006), whose structure, parameters and associated uncertainty will be determined during the training process.

The problem of passive robust fault detection using models and the knowledge regarding their parameter uncertainty has mainly been addressed by checking if the measured behaviour is inside the region of possible behaviours following the so-called *forward test* since it is based on bounding the direct image of an interval function (Armengol et al., 2000; Travé-Massuyès and Milne, 1997; Puig et al., 2002; Escobet et al., 2001; Adrot et al., 2000; Ploix et al., 2000; Witczak et al., 2006). The main contribution of this paper is to introduce a *backward test* (based on bounding the inverse image of an interval function) that allows checking if there exists a parameter in the uncertain parameter set that is consistent with the measured system behaviour. This test is implemented using interval constraint satisfaction algorithms (Jaulin et al., 2001), which can perform efficiently in deciding if the measurements are consistent with the GMDH model and the associated uncertainty. Finally, this approach is tested on several real fault scenarios of a servoactuator being a FDI benchmark in the European Project DAMADICS. The paper is organized as follows: Section 2 outlines the idea of robust fault detection with GMDH neural networks designed with the bounded-error parameter estimation technique. In Section 3, the ideas of forward and backward fault detection tests are discussed in the context of their application to the design of the GMDH neural network-based fault detection schemes. Section 4 presents the proposed approach to the implementation of the backward fault detection test that is based on the constraint satisfaction technique. Section 5 presents a comprehensive study regarding the application of the proposed approach to the DAMADICS benchmark problem. Finally, Section 6 is devoted to conclusions.

2. Robust model-based fault detection using GMDH neural nets

2.1. Model-based fault detection principle

Model-based fault detection is based on the generation of a discrepancy between the measured and estimated process behaviours using a model. This discrepancy is known as a *residual*. A *residual generator* can be constructed by

$$r(k) = y(k) - \hat{y}(k), \tag{1}$$

where $y(k) \in \Re$ and $\hat{y}(k) \in \Re$ are the measured and estimated outputs, respectively. The residual signal should be normally close to zero in the fault free mode, otherwise it should be distinguishably different from zero when a fault occurs. The residual should ideally carry an information about fault only.

2.2. Robustness issues

The presence of disturbances, noise and modelling errors causes that the residuals become nonzero and interfere with the detection of faults. Therefore, the fault detection procedure has to be *robust* in the face of these undesired effects. Robustness can be achieved, as discussed in the Introduction, in the residual generation (*active robustness*), or in the decision-making stage (*passive robustness*) (Chen and Patton, 1999). The passive approach, when considering the uncertainty described by a parameter vector $\boldsymbol{\theta}$ contained in the compact set $\boldsymbol{\Theta}$, i.e. $\boldsymbol{\theta} \in \boldsymbol{\Theta} \subset \Re^{n_p}$, is based on propagating the effect of uncertainty to the estimated output such that

$$y(k) \in [\underline{\hat{y}}(k), \overline{\hat{y}}(k)] \tag{2}$$

or, equivalently to the residual:

$$\begin{aligned} r(k) = y(k) - \hat{y}_c(k) &\in [-\Delta\hat{y}(k), \Delta\hat{y}(k)] \\ &= [\underline{r}(k), \bar{r}(k)], \end{aligned} \tag{3}$$