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Fuzzy fault isolation using gradient information and quality criteria from system identification models

Francisco Serdio [a], Edwin Lughofer [a,*], Kurt Pichler [b], Markus Pichler [b], Thomas Buchegger [b], Hajrudin Efendic [c]

[a] *Department of Knowledge-Based Mathematical Systems, Johannes Kepler University Linz, Austria*
[b] *Linz Center of Mechatronics GmbH, Austria*
[c] *Institute for Design and Control of Mechatronical Systems, Johannes Kepler University Linz, Austria*

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ABSTRACT

In this paper, we propose a new approach to Fault Isolation (FI) based on *isolation indicators* extracted from multi-dimensional system identification models. Given a set of models pointing to a fault (called *violated models*), the indicators comprise the following information: (1) the degree of violation of the actual samples in all violated models, (2) the quality (trustworthiness) of the violated models and (3) the influence of each variable across all violated models, measured by amalgamated gradient information. We propose two variants of our FI approach: a crisp variant which uniquely determines the variable/channel where the fault is most likely to have occurred, and a fuzzy variant which provides a descending list of fault likelihoods over all variables/channels in the violated models. We evaluated our approach using various types of data-driven modeling techniques (ridge regression, PLS, fuzzy systems approximation) for setting up the system identification models and a Fault Detection (FD) scheme based on a dynamic on-line analysis of residual signals extracted from the models. The evaluation is based on real-word data sets recorded at two different multi-sensor networks that include fifty measurement channels (system variables) in average: one installed for condition monitoring at rolling mills and one for supervising driving simulation cycles at engine test benches. An important aspect of our FI approach is that it can be applied to any FD system that uses reference models –these can be analytical, expert-based or data-driven– provided that some quality information criteria (model-based and sample-based) are available.

1. Introduction

In modern industrial systems, complexity is increasing as multi-sensor network systems are expanding towards large-scale systems [11] and high-speed frequency recordings result in on-line data streams [16]. Automatic condition monitoring [23,55,13,38] is thus becoming an increasingly attractive topic, since it guarantees stable and smooth processing and prevents system failures which may not only lead to damage to production items, but also to severe risks and danger to

* Corresponding author.
E-mail addresses: francisco.serdio@jku.at (F. Serdio), edwin.lughofer@jku.at (E. Lughofer), kurt.pichler@lcm.at (K. Pichler), markus.pichler@lcm.at (M. Pichler), thomas.buchegger@lcm.at (T. Buchegger), hajrudin.efendic@jku.at (H. Efendic).

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operators and system users. With proper and accurate condition monitoring, that is, early detection of faults in industrial systems, costs for repairs can be minimized and production efficiency increased. Nowadays, a fully automatized monitoring system is indispensable, as manual inspection is too time- and cost-intensive due to high system complexities: in many cases, a few hundred measurement channels across the system must be supervised [27].

Fault Detection (FD) plays a central role in condition monitoring systems, as it informs the operators that something atypical or abnormal is happening in the system and to proceed with care. The subsequent components such as fault isolation (which identifies where the fault has most likely occurred), fault identification (which types of fault have occurred) [40], fault reasoning (the reason of a fault) [28] and fault reaction (feedback loop to the process to correct erroneous behavior) are then triggered by FD only when a fault is present. Automatic FD using different types of pre-conditions (such as fault patterns or fault models) and different types of system models (analytical, frequency-based, data-driven oriented, visual-based, evolving, etc.) has been handled in various books and publications, see [24,12,10,28,9,13,35,29].

Once a fault is detected, isolating it, that is, identifying the system variables (often reflected in measurement channels) or combination of variables which are responsible for the process abnormality, helps the system operator to determine which part(s) should be repaired or replaced (localization). This enables fast reaction to system faults and thus may prevent various kinds of damages to the system.

State of the Art. If *univariate systems models* or *univariate analysis tools* are used, each measurement channel is examined separately and independently of the others and FI becomes trivial: whenever a model is violated or points to potential faults in the system, the responsible channel (i.e., system variable) is automatically known. However, the problem with univariate methods is that their performance is usually much poorer than that of multivariate techniques, since they do not consider any interrelations and dependencies between channels, which allow faults to be seen and thus identified more easily. This was, for instance, analyzed in [49,8] in the context of residual-based FD for various application scenarios; there, auto-regressive univariate models (of the ARMA type [56]) achieved of about 25–30% lower FD rates than higher dimensional system identification models.

Previous work in the field of *multi-variate methods* relied on examining the contribution of the original channels to the observable characteristic of the system that has exceeded a control limit. This was the approach followed in [41], where the authors implemented a process variable contribution plot for linear PCA describing the change in the new observation variables relative to average values calculated from the nominal model. This work was successfully extended in [25] to the non-linear PCA case. However, PCA-based FD showed relatively poor performance for particular measurement signals, including untypical occurrences such as abrupt changes in the patterns (see [49] for details); only in the case of smooth continuous measurement signals it can achieve good performance and compete with residual-based approaches [44].

Other FI approaches rely on analytical fault and isolation models [12,24,28], which are, however, usually very system-specific and require significant manpower for model setup. Another group of approaches (e.g., [2,18]) relies on the usage of *fault signatures*, which require expert knowledge about the process, more specifically about the appearance of faults either directly in the measurements or, more often, in the residual signals (observed versus predicted values). Linear models frequently serve as a baseline, and a Bayesian extension of this reconstruction-based contribution approach has recently been provided in [18]. However, in practice such fault signatures are rarely available and often require time-intensive off-line pre-simulation and validation phases to gain insights how the faults may appear in the residual signal(s).

Our Approach. We investigated a new kind of FI algorithm which is based on on-line residuals extracted from SysID models within an FD framework built upon the approach demonstrated in [49,50]—see also Section 2 for a compact summary.

The FI component described in this paper serves as an add-on in this framework and relies on time-lagged dynamic prediction models (obtained by data-driven regression techniques) [50], which may become violated in on-line mode, i.e., showing untypical residuals pointing to potential fault candidates. All *violated models* are used in the FI process, as the degree of influence of each system variable included in them is examined. The *isolation indicators (likelihoods)* are calculated for each model separately by a weighted combination of.

- model gradients (along each input variable) in the current samples
- model quality, measured by the coefficient of determination R2, and
- degree of model violation measured by the distance between the residuals and the dynamic tolerance band surrounding them,

and are then accumulated over all the violated models. The variables with the highest indicators are expected to be those which are affected most by system failures. The motivation for using the *gradient* as valuable information for the degree of variable influence is based on the fact that significant deviations from the nominal fault-free case resulting in high residuals (and thus falling outside the tolerance band) are most likely caused in those variables which have a high influence in the model. The motivation for weighting the variables' influences (contributions) with the respective *model qualities* is that, usually, multiple models with different approximation qualities and thus different prediction uncertainties are violated. Variables in models with higher quality and certainty should therefore have a higher impact on the FI process.