Learning-based Model Matching for Fault Detection and Isolation of Nonlinear Systems

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Summary. This abstract presents a method for fault detection and isolation (FDI) in nonlinear uncertain systems. The proposed method has two stages: first, an offline training of a static map to capture the unstructured uncertainty; second, an online fault detection, isolation, and estimation scheme. A nonlinear mechanical benchmark system is used to illustrate the performance of the scheme.

Introduction

The reliable functioning of high-tech systems can only be achieved through predictive maintenance, for which techniques for fault detection (is a fault occurring?) and fault isolation (what is the fault source?) are essential prerequisites [1]. We aim to develop a hybrid (physics-learning) fault detection and isolation (FDI) scheme that provides superior monitoring performance by leveraging cutting-edge machine learning (ML) algorithms and first-principles physics-based models. This abstract is organized as follows. First, the problem formulation is elaborated. Then, the proposed methodology is briefly presented. Next, the proposed method is evaluated by a benchmark FDI problem using simulation results. Finally, concluding remarks are discussed.

Problem Formulation

Consider a nonlinear dynamical system of the form:

$$\begin{cases} \dot{x}(t) = g(x(t), u(t)) + \eta(x(t), u(t)) + \omega(t) + \phi(x(t), u(t), t), \\ y(t) = x(t) + \nu(t), \end{cases} \tag{1}$$

where $t \in \mathbb{R}^+$, $x \in \mathbb{R}^{n_x}$, $y \in \mathbb{R}^{n_x}$, $u \in \mathbb{R}^{n_u}$ are time, state, measured output, and known input vectors, respectively, and $n_x, n_u \in \mathbb{N}$. Function $g : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \mapsto \mathbb{R}^{n_x}$ is a known nonlinear function. Function $\eta : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \mapsto \mathbb{R}^{n_x}$ represents unknown model uncertainty. Functions $\omega, \nu : \mathbb{R}^+ \mapsto \mathbb{R}^{n_x}$ are unknown disturbances, and function $\phi : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \times \mathbb{R}^+ \mapsto \mathbb{R}^{n_x}$ is the unknown process fault.

Methodology

The proposed methodology has two stages: 1. offline uncertainty learning, and 2. online FDI scheme (see Fig. 1). First, in the offline learning stage, a static map for unstructured uncertainty is trained on the basis of the healthy system input and output data (i.e., for the system with $\phi = 0$). We use a supervised method (i.e., linear regression in this abstract) to find the static map from system input and output to uncertainty in the training phase. Labeled data for the supervised learning of the model uncertainty is obtained using the known part of the system dynamics and healthy system input and output historical data. Then, in the online stage, we estimate the fault by matching the faulty model and the approximately known model of the healthy system (which is constituted by a physics-based model and the trained uncertainty model). Based on the estimated fault signal, the fault can be detected and isolated using the CUSUM-based procedure [3] as a change detection method.

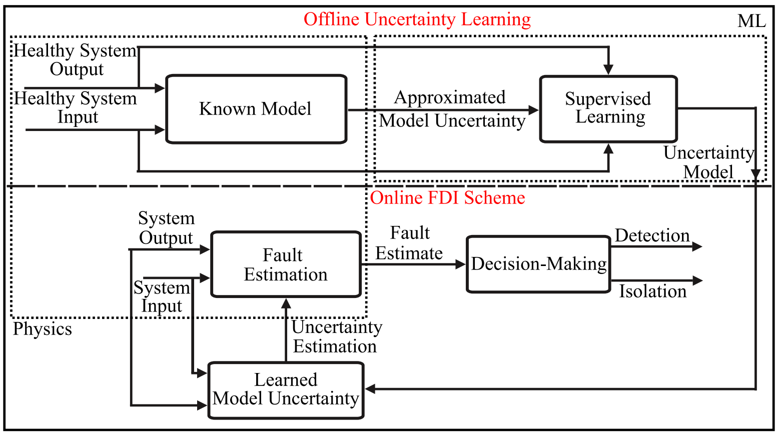

Figure 1: Offline uncertainty learning and online FDI scheme block diagrams.

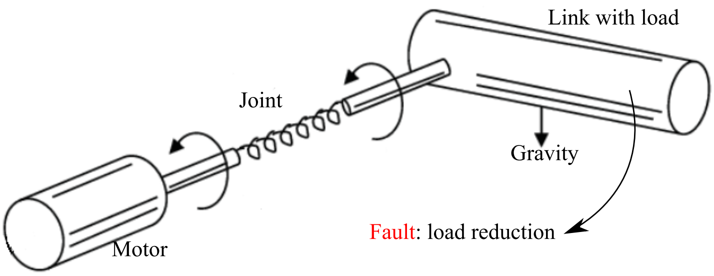

Figure 2: The nonlinear benchmark schematic.

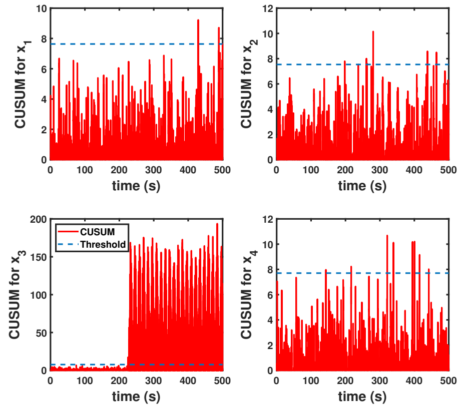

Figure 3: The CUSUM sequences and the thresholds.

Simulation Results

In what follows, the methodology is applied to a nonlinear benchmark system (a single-link robotic arm with a revolute elastic joint, see schematic in Fig. 2) [2]. This system has the structure introduced in (1) and four states, $x(t) = [x_1(t), x_2(t), x_3(t), x_4(t)]^T$. In the simulation, a fault is induced in the third equation of the right-hand side of (1). The fault, which reduces the link mass, occurs abruptly at 225 seconds. The CUSUM-based thresholds and sequences for each state are depicted in Fig. 3. The CUSUM sequence is a cumulative sum of the estimated fault, which is compared to the CUSUM threshold for fault detection. It is clear from the left-down plot of the figure that the fault can be detected by the proposed method since the CUSUM sequence exceeds the threshold after the fault occurrence. Furthermore, to indicate the capability of the proposed method, it is compared with a linear conventional observer-based FDI method to detect a small fault (Fig. 4). This small fault is the same as the previous fault. However, its magnitude is one-fifth of the previous one. It can be seen in the figure, unlike the proposed method, the linear method cannot detect the fault due to ignoring the nonlinearity and uncertainty.

Conclusions

The proposed methodology for FDI of nonlinear systems has improved fault detectability compared to conventional methods in the presence of nonlinearity and uncertainty for the benchmark system.

Acknowledgment

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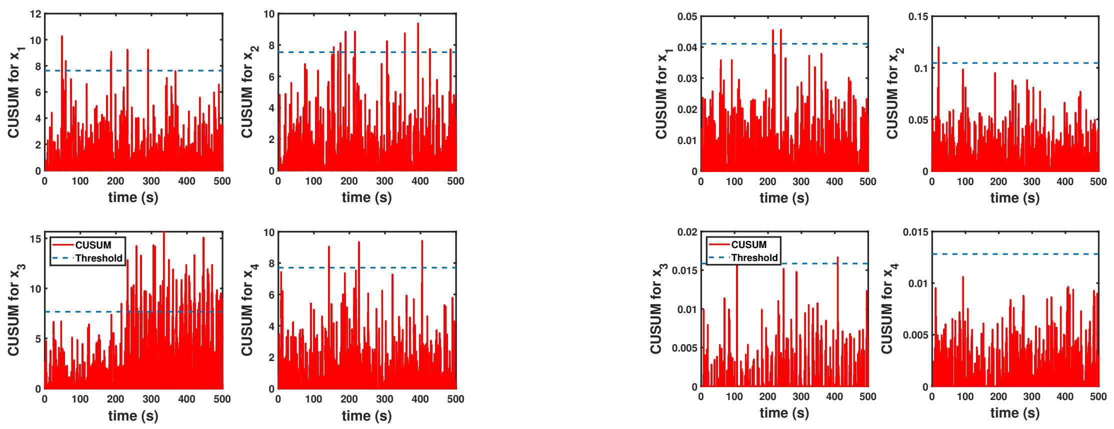

(a) The proposed method.

(b) The linear observer.

Figure 4: The CUSUM sequence for the small fault and the thresholds.