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Multiple sensor fault diagnosis by evolving data-driven approach

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ABSTRACT

Sensors are indispensable components of modern plants and processes and their reliability is vital to ensure reliable and safe operation of complex systems. In this paper, the problem of design and development of a data-driven Multiple Sensor Fault Detection and Isolation (MSFDI) algorithm for nonlinear processes is investigated. The proposed scheme is based on an evolving multi-Takagi Sugeno framework in which each sensor output is estimated using a model derived from the available input/output measurement data. Our proposed MSFDI algorithm is applied to Continuous-Flow Stirred-Tank Reactor (CFSTR). Simulation results demonstrate and validate the performance capabilities of our proposed MSFDI algorithm.

1. Introduction

Modern systems and industrial processes rely heavily on sensors used for monitoring and control purposes and the ever-increasing complexity of these systems calls for the use of more and more sensors. Sensors play an important role in a closed-loop control system where the actual value measured by a sensor is constantly compared against the reference value, and the controller is used to minimize the error between these values. Integrity of sensor data is therefore of paramount importance in modern applications [1,2] since invalid measurement data from a sensor can cause problems in the closed-loop system and results in inappropriate corrective action by the controller. Therefore, the integration of sensor and control system in intelligent manufacturing processes requires means for sensor fault diagnosis. Nowadays, the trend is to apply the Condition Based Maintenance (CBM) in complex processes in order to minimize downtime and maximize profit. Given that CBM relies on information provided by sensors, the reliability of them must be taken in the consideration when adopting the CBM approach. The nonlinear and dynamic behavior of the process makes multiple sensors fault detection and isolation a challenging task as the nonlinearity of the process is reflected on the data provided by sensors; leading to possible confusion between nonlinearity and sensor fault itself.

Recently, the data-driven methods (neural networks, principle component analysis, etc.) have been successfully used in sensor fault diagnosis [3]. These methods are very useful and flexible for sensor fault detection and isolation, and require only a limited historical data from sensors of the plant without a need for deep understanding of the process. Different data-driven methods have been applied to extract features directly from the past and current data to detect and isolate sensor faults. The Neural-Network (NN) has been applied to sensor fault detection and isolation by making use of the ability to learn from historical and actual measured variables to take decision about the reliability of the sensors in complex/nonlinear

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context [4–6]. Nevertheless, the concept of NN has the drawback of slow training and the design of an NN is more of an art than a science. Another data-driven tool is the Takagi–Sugeno (TS) model which is an universal approximator of nonlinear function [7]. The TS provides an efficient and computationally attractive solution to fault diagnosis and prognosis [8,9]. The efficiency of any fault diagnosis algorithm is highly dependent on its ability to perform good prediction. Recent developments confirm the ability of using TS model to predict nonlinear time series and it has been shown and validated in [10,11] that the TS is a powerful approach in comparison with neural network and traditional statistical approaches (AR, ARMA, ARIMA, etc.). Also TS surpasses other methods in both prediction accuracy and training efficiency and the authors in [9] demonstrate that the TS is a very reliable and robust machine health condition predictor.

In this work we have adopted the TS model adjusted by evolving approach [12] as a promising model to detect and isolate sensor fault. The choice of the evolving approach as learning algorithm for the TS is based on the following reasons [13]: (i) it does not require the user to define the structure of the TS model, (ii) it does not need a complete learning data set to start the identification process of the TS model (i.e., the approach can be started from scratch), and (iii) it has very low memory requirements, due to recursive calculations.

This work aims to develop and design a Multiple Sensor Fault Detection and Isolation (MSFDI) model based on multiple evolving Takagi–Sugeno (eTS) models in nonlinear process applications. Towards this goal, a new approach for stopping the training phase of the eTS is proposed and then, a novel method for fault detection and isolation is developed. The paper is organized as follows. In Section 2, data-driven residual generation schemes are explained and the evolving Takagi–Sugeno (eTS) model is presented. In Section 3, a proposed sensor fault diagnosis method is presented based on a multiple eTS model. Section 4 demonstrates simulation results corresponding to sensor fault detection and isolation in a Continuous-Flow Stirred-Tank Reactor (CFSTR) system.

2. eTS applied to Sensor Fault Diagnosis (SFD)

2.1. Generating the residuals

In data-driven based methods (Fig. 1), a set of residuals is generated where each residual is the difference between the observed behavior (measured value) and the one predicted by the identified mathematical model (*Black Box*: eTS):

$$r_j = S_j - \widehat{S}_j, \quad j \in 1, \ldots, M, \tag{1}$$

where M is the number of sensors, S_j is the output of the jth sensor and $\widehat{S}_j$ is the estimated value. The residual generation can be obtained by eTS in which, it is possible to attain a white noise characteristic for the residuals in the presence of noise, in the absence of fault, and with high nonlinear/complex system. Let us consider a system with the input variables vector $U = [u_1, \ldots, u_p]^{\mathrm{T}}$ and the output variables vector $Y = [y_1, \ldots, y_q]^{\mathrm{T}}$. For the complex dynamical system, only the input–output data is available, namely

$$Z^{\mathrm{T}}(t) = [Y^{\mathrm{T}}(t), U^{\mathrm{T}}(t)] \quad t = 0, 1, 2, \ldots \tag{2}$$

It is assumed that each sensor value can be described by

$$S_j = f_j^*(Z(t), \ldots, Z(t-s)), \tag{3}$$

where f_j^* is the true function of jth sensor. In real applications, one can never find the correct expression for the function f_j^*. However, the past values of $Z(t)$ can be used to construct the nonlinear predictor model ($\hat{f}_j$) using the eTS approach. Hence, the role of this model is to predict the actual sensor value where the output of the model is generated by

$$\widehat{S}_j = \hat{f}_j(\varphi, \Gamma), \tag{4}$$

where Γ is the vector of parameters model, and φ is the regression vector:

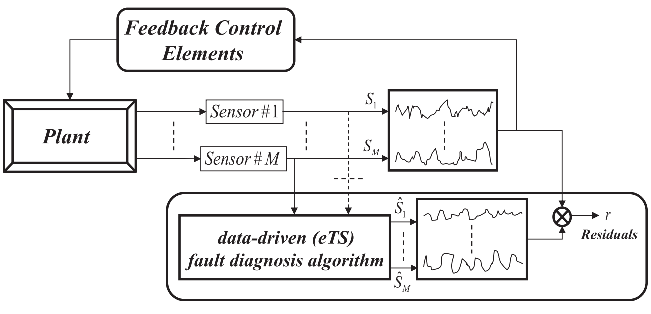

Fig. 1. Generating the residuals by data-driven analytical redundancy.