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An ensemble approach to sensor fault detection and signal reconstruction for nuclear system control

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ABSTRACT

To efficiently control a process, accurate sensor measurements must be provided of the signals used by the controller to decide which actions to actuate in order to maintain the system in the desired conditions. Noisy or faulty sensors must, then, be promptly detected and their signals corrected in order to avoid wrong control decisions. In this work, sensor diagnostics is tackled within an ensemble of Principal Component Analysis (PCA) models whose outcomes are aggregated by means of a local fusion (LF) strategy. The aggregated model thereby obtained is used for both the early detection and identification of faulty sensors, and for correcting their measured values. The fault detection decision logic is based on the Sequential Probability Ratio Test (SPRT). The proposed approach is demonstrated on a simulated case study concerning the pressure and level control in the pressurizer of a Pressurized Water Reactor (PWR). The obtained results show the possibility to achieve an adequate control of the process even when a sensor failure occurs.

1. Introduction

When a fault occurs in a sensor whose measurements are used for the control of an industrial process, a repair action must be promptly initiated since the use of incorrect information by the controller could compromise the correct functioning of the process, with potential fallbacks both on production and safety. In this context, on-line monitoring methods can provide an indication of the health of the sensors and supply an early warning of incipient faults, thus enabling to assess the reliability of the measurement and to opportunely plan the sensor maintenance. Additionally, for continuing operation while reparation is performed, the erroneous measurements should be substituted by accurate estimates of the signal true values.

The main objective of this work is to devise an on-line monitoring scheme to reduce the effects of sensor faults on the process control, by detecting the faults and by reconstructing the correct signal values. Three steps are envisaged: (a) validate the sensor measurements, (b) detect and identify faults and (c) reconstruct the correct values of the faulty signals. Steps (a) and (c) can be performed by resorting to a model that generates estimates of the correct sensors signal values based on actual readings and correlations among them; step (b) can be performed by a fault detection and identification module which determines, as early as possible, whether the sensors are behaving anomalously and identifies the faulty ones among them.

Concerning the development of a signal validation and reconstruction model, a common approach is that of using auto-associative models (Hoffmann, 2006; Holbert and Upadhyaya, 1990; Roverso et al., 2007). The practical problem, however, is that a single auto-associative model cannot handle the multiplicity of signals measured on a real plant (Baraldi et al., 2008; Fantoni and Mazzola, 1996; Fantoni et al., 2003; Zio et al., 2007). A possible way to overtake this limitation is to subdivide the signals into small overlapping groups, develop an ensemble of models, one for each group, and finally combine their outcomes. Key to building of the ensemble is the *diversity* of the individual models. In the approach investigated in this work, diversity is promoted by randomly generating the signals groups according to the Random Feature Selection Ensemble (RFSE) technique (Bryll et al., 2003); this is a completely random technique in which no optimization of the composition of the individual groups is sought, i.e., no relevance is given, for example, to the correlation between the signals in the groups or to their capability of reconstruction. The groups thereby created are used to develop a corresponding number of signal validation and reconstruction PCA models (Jolliffe, 2002; Diamantaras and Kung, 1996; Scholkopf et al., 1999; Moore, 1981). The outcomes of different models are then aggregated using a LF method (Baraldi et al., 2009; Bonissone et al., 2008). To improve the accuracy of the reconstruction, past signal measurements are used as further input to the models and the reconstruction of the faulty signals is iterated until satisfactory convergence.

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The detection and identification of a sensor fault can be achieved by comparing the actual sensor measurements with the signal values estimated by the signal validation and reconstruction model; in this work, the Sequential Probability Ratio Test (SPRT) which considers the statistical properties of the residual, i.e., the difference between the measurements and their estimation, is used.

The proposed approach has been applied to a case study concerning the level and pressure control in the pressurizer of a PWR nuclear power plant. In order to test the effectiveness of the described procedure, faults have been added to sensors whose signals are simulated using a Matlab SIMULINK model of the pressurizer. Upon fault detection, the reconstructed value of the faulty signal is used by the controller to decide the control action. A comparison is made of the control performance obtained when feeding the controller with the measurements coming from the faulty sensor or the reconstructed values.

The remaining parts of the paper are organized as follows. Section 2 states the problems of fault detection, identification and signal reconstruction in the frame of process control; Section 3 describes the signal validation module, recalling briefly the RFSE and LF techniques; Section 4 describes the SPRT technique implemented in the fault detection module; Section 5 presents the results from a set of experiments concerning the control of a simulated PWR pressurizer in presence of faults of the sensors; finally, Section 6 presents the conclusions and describes potential future directions of research.

2. Sensor fault detection, identification and signal reconstruction for process control

The objective of a controller is to correct the mismatch between the true values $f_{i_C}^T$ of n_C plant variables and their reference values (setpoints) $f_{i_C}^{Ref}$ by establishing and actuating corrective actions. In order to decide the opportune control actions, the controller considers the available information describing the state of the process to be controlled. Let us assume that this information is characterized by the measured values f_{i_I} of n_I plant signals, hereafter called controller input signals. For efficient control of the process, the controller should be fed with the best available estimate of the true values $f_{i_I}^T, i = 1, \ldots, n_I$ of each controller input signal. Since a sensor measurement f_{i_I} provides an estimate of the true value $f_{i_I}^T$ of the physical quantity used by the controller, ideally it should be $f_{i_I} = f_{i_I}^T$, but in practice the measurement f_{i_I} is affected by random noise and sometimes it also deviates from the true value $f_{i_I}^T$ because of a sensor fault.

Fig. 1 shows the general framework adopted to address the problem of detecting and identifying faults in the sensors measuring the controller input signals f_{i_I}, and eventually reconstructing their correct values $f_{i_I}^T$.

Let us assume that n signals of the process under analysis are measured and let f_i be the measurement of the generic ith signal, $i = 1, \ldots, n$; notice that the n_I controller input signals are contained in this set of n signals. The n measured signals f_i are processed by a signal validation and reconstruction model which provides a first estimate $\hat{f}_i^1$ of the true signal value f_i^T based on the correlation existing between the n measured signals. These correlations are "learned" by the model from a "training" data set $\mathbf{X}_{TRN}$ containing faults-free measurements of the n signals recorded during normal operation of the system.

In order to catch the dynamic evolution of the system and increase the robustness of the method, the set of measurements f_i which are given in input to the signal validation and reconstruction model is constituted not only by the current values $f_i(t)$ of the n measured signals, but also by the $n \cdot T$ values $f_i(t-1), \ldots, f_i(t-T)$ measured in a sliding window of T previous time instants (Fig. 2).

The n estimates $\hat{f}_i^1(t)$ generated by the signal validation and reconstruction model are compared with the measured values $f_i(t)$ of the current signals values $f_i^T(t)$ and the residuals $e_i(t) = f_i(t) - \hat{f}_i^1(t)$ are used as input to the fault detection module. By monitoring the evolution of the statistical properties of the residuals e_i, the conditions of the sensors are verified and an indication about their state of health is obtained. When one or more sensors are diagnosed as faulty, their measurements are not reliable and should be substituted by the estimates produced by the validation and reconstruction model. However, since the estimates $\hat{f}_i^1$ produced by the signal validation and reconstruction model can

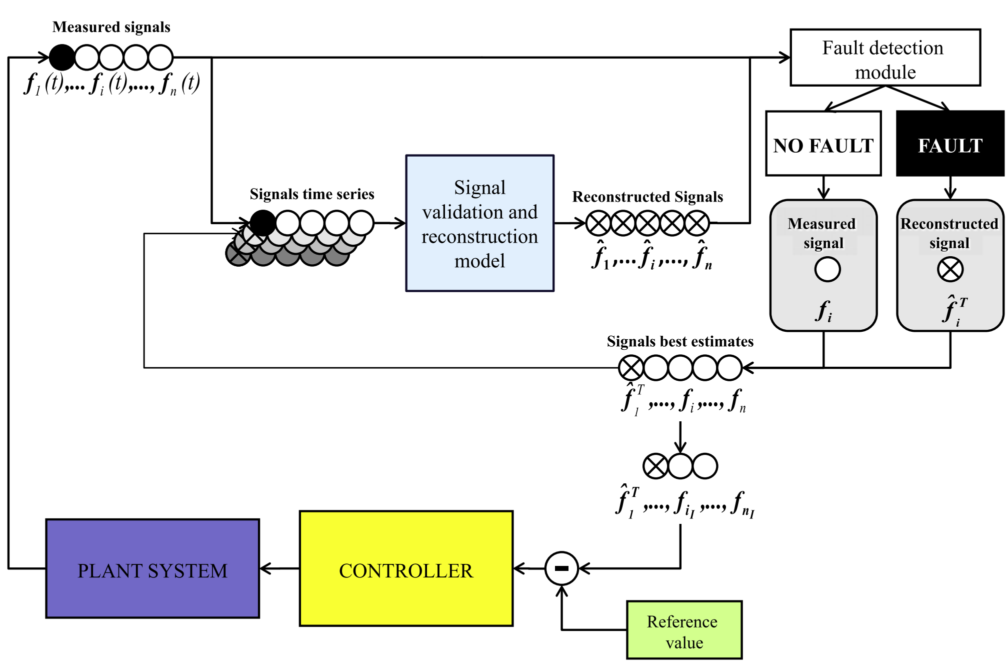

Fig. 1. Fault detection, identification and signal reconstruction strategy in case of sensor faults; the black bullet indicates a fault.