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Sensor fault detection in Nuclear Power Plant using statistical methods

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ABSTRACT

In this paper, a sensor fault detection and isolation technique is proposed using statistical methods. An enhanced reconstruction method is proposed using Singular Value Decomposition (SVD). In the traditional SVD reconstruction method, the faulty data may affect other fault free data. The enhanced SVD (ESVD) reconstruction method is a robust method to map as a normal data. The statistical hypothesis test, namely Generalized Likelihood Ratio Test (GLRT) is applied to detect the fault in the residual space. The proposed method performance is verified by the real data of Fast Breeder Test Reactor (FBTR).

1. Introduction

Continuous sensor health condition monitoring provides a variety of benefits such as improved reliability, improved safety, reduced unnecessary periodical sensor calibration testing. For monitoring and controlling application of a complex production system, a large number of distributed sensors are used to provide chronological and spatial information. However, along with the benefit of using distributed sensors, there are some risks because of the severe consequences may arise, if the signals provided by sensors are out of calibration. A faulty sensor can provide an inappropriate information that can affect the system supervision and decisions making. Therefore, continuous monitoring of the performance of the sensor, i.e., sensor fault detection and localization are important issues in current research work.

In the literature, sensor fault detection and isolation are broadly classified into two categories: model-based method and data-driven method. In the model-based method, a mathematical model is designed based on the physical representation of the process variables. They include Kalman filter (Hajiyev and Caliskan, 2000; Salahshoor et al., 2008; Saravanakumar et al., 2014), parity equation (Gertler, 1997; Odendaal and Jones, 2014), Luenberger observer-based (Tarantino et al., 2000; Alkaya and Eker, 2014) and state observer-based approach (Zarei and Poshtan, 2011). The application of model-based depends upon the availability of the model because, in a complex system, it is very difficult to get an exact mathematical model. Another approach for fault detection is the data-driven method. This is based on historical data, not necessarily the good knowledge about the physical representation of the process parameters. In general, data-driven methods are identified the faulty sensor using classification and data redundancy techniques. In classification technique, the faulty data are segregated from the normal data. Several classification methods are applied in fault detection; these include Support Vector Machine (SVM) (Banerjee and Das, 2012; Yin et al., 2014; Namdari and Jazayeri-Rad, 2014), Neural Network (Fast and Palme, 2010; Palmé et al., 2011) and Deep Learning (Tamilselvan and Wang, 2013; Shang et al., 2014). The classification methods are detected faulty data, not the faulty sensor and the classification accuracy depends on the complexity of the data, i.e., heterogeneity, non-linearity and dimensionality of the data. Therefore, data reconstruction methods are practical for fault detection in industrial application. Data redundancy may produce two ways, one is data approximation and another is data reconstruction. The data are approximated by different types of artificial neural network (ANN) learning techniques, like Back-propagation Neural Network (BPN) (Wu and Saif, 2005), Auto-Associative Neural Network (AANN) (Huang, 2004), Cascade Neural Network (CNN) (Hussain et al., 2015), and Recurrent Neural Network (RNN) (Talebi et al., 2009). These methods are computationally complex and have some parameters. This is difficult to update the model, because, in many industrial applications of condition monitoring such as Nuclear Power Plants, it is common to update the model periodically in order to follow gradual medication of signal characteristic. On the other hand, data reconstruction models are less computation complexity. For data reconstruction, several statistical techniques are employed, they are Principal Component Analysis (PCA) (Harkat et al., 2006; Tharrault et al., 2008; Harrou et al., 2013), Auto-Associative Kernel Regression (AAKR) (Garvey et al., 2007; Maio et al., 2013), and Partial Least Square (PLS) (Muradore and Fiorini, 2012).

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Among them, AAKR based reconstruction is efficient to map as a normal data. Baraldi et al. (2015) noticed that the reconstructed signal by AAKR is affected by drift trend, they assume the values in the middle of drifted and expected values. In PCA reconstruction, the reconstructed data are not mapped to normal data, because selected principal components are unable to capture the important features of the data. Recently, Harrou et al. (2013) noticed that the PCA reconstruction model with the Generalized Likelihood Ratio Test (GLRT) fault detection performance is desirable. The reconstruction error is adjusted by the GLRT. The PCA-GLRT is superior to PCA-T^2-statistic and PCA-Q-statistic (Harrou et al., 2013). But, the accuracy depends on the choice of principal components, and heterogeneity, non-linearity, and dimensionality of the data. To overcome these difficulties, an alternative data reconstruction method, namely singular value decomposition (SVD) was proposed (Mandal et al., 2017b). Jha and Yadav (2011) were noticed that SVD based reconstruction is an effective tool for denoising the signal. But in faulty data reconstruction, the few faulty points of a sensor may affect the whole data points of that signal, which may produce false alarms. In this paper, an enhanced SVD (ESVD) based reconstruction method is proposed for thermocouple sensor fault detection in Fast Breeder Test Reactor (FBTR). The major contributions of this paper are as follows:

- An enhanced reconstruction method ESVD is proposed for data reconstruction.
- The effective statistical hypothesis test, generalized likelihood ratio test (GLRT) is applied as a fault detection metric.
- The proposed method ESVD-GLRT is superior to PCA-GLRT and SVD-GLRT for fault detection.

This paper is organized into five sections including the present one. The next section presents the brief description about the FBTR. Section 3 represents the proposed method using ESVD based reconstruction and GLRT. The result and discussion of the proposed method with comparison the existing method is given in section 4. The final conclusion of this paper and recommendations for future research work is given in section 5.

2. Brief description of FBTR

The FBTR uses plutonium-uranium mixed carbide as fuel and liquid sodium as a coolant. The entire system is broadly divided into three systems: primary sodium system, secondary sodium system, and steam and water circuit. The important components of the primary sodium system are the reactor assembly, two intermediate heat exchangers (IHX), two sodium pumps and interconnecting piping. The secondary system includes sodium pumps, re-heaters, surge tanks, steam generator and connecting piping. The heat generated in the fuel sub-assemblies are removed by circulating liquid sodium through the reactor core. Two centrifugal pumps are used to pump sodium through the fuel sub-assemblies in the reactor core. Three thermocouples are used to measure the sodium temperature at the inlet of the reactor core. The central fuel sub-assembly contains four thermocouples (Tna000X, Tna000Y, Tna000Z, and Tna000W) at the outlet and the rest of each 84 fuel sub-assemblies contain two thermocouples (Tna0nX, Tna0nY, for n = 01 to 84) at the outlet. Chromel-Alumel type thermocouples are used to measure the temperature of sodium at the inlet of the reactor core and at the outlet of the fuel sub-assemblies. The schematic diagram of the FBTR is depicted in Fig. 1.

In this work, thermocouple sensor fault detection is proposed using statistical methods. The proposed method is based on data reconstruction. The next section explains the data reconstruction technique using principal component analysis and singular value decomposition.

3. Proposed method

The SVD is an effective tool for denoising in image processing, signal processing, and statistical analysis. It is used to map the data into the normal data by removing noise and outlier by reconstruction technique (Mandal et al., 2017b). The proposed fault detection technique is based on a data reconstruction technique. The ESVD based data reconstruction method is applied. The fault detection process consists of two steps: (i) residual generation, and (ii) residual evaluation. Residual is generated by reconstructing the data using the ESVD method. The deviation of reconstructed data from the original is called residual. The residual space is tested by the GLRT to detect the faulty sensor. The block diagram of the proposed method is given in Fig. 2. The reconstruction of the proposed method is compared with PCA and SVD. The idea of the ESVD reconstruction method is same as the PCA reconstruction method. The next subsection explains the data reconstruction by the PCA, SDV, ESVD, and the statistical hypothesis test GLRT for fault detection.

3.1. Data reconstruction using PCA

The PCA is a widely used statistical tool for dimension reduction and data reconstruction. PCA is used to project the data into a lower dimensional linear space such that the variance of the projected data is maximized. Equivalently, it is the linear projection that minimizes the average projected cost, i.e. mean squared distance between the data points and their projections. Let $\boldsymbol{X}$ be a data matrix with dimension $M \times N$, where M is the number of observations and N is the number of variables. The data samples are considered as $\vec{x}_1, \ldots\ldots \vec{x}_M$ in a N-dimensional space, where the mean is computed as $\vec{\mu} = \frac{1}{M}\sum_{i=1}^{M}\vec{x}_i$ along with their covariance $\boldsymbol{C} = \frac{1}{M}\sum_{i=1}^{M}(\vec{x}_i - \vec{\mu})(\vec{x}_i - \vec{\mu})^T$. The eigenvalues and eigenvectors are computed from the covariance matrix $\boldsymbol{C}$ by eigenvalue decomposition or SVD. The SVD is computed the eigenvalues and eigenvectors as:

$$\boldsymbol{C} = \boldsymbol{U}\Sigma\boldsymbol{V}^T \tag{1}$$

where $\boldsymbol{U}$ and $\boldsymbol{V}$ are the ortho-normal and Σ is the diagonal matrix of eigenvalues in descending order i.e. $\lambda_{11} > \lambda_{22} > \ldots > \lambda_{NN}$. The matrix $\boldsymbol{C}$ is a symmetric matrix, so the eigenvalues are real and the eigenvectors are orthogonal. Also, by construction, the matrix $\boldsymbol{C}$ is positive semi-definite so, $\lambda_{NN} \geq 0$, i.e. eigenvalues are nonnegative.

Thus, for the problem at hand to use a PCA approach is to represent the data $\boldsymbol{X}$ in a different space (p dimensional, $p < N$) using a set of principal orthogonal vectors $\vec{v}_i$ of $\boldsymbol{V}$ corresponding to largest eigenvalues. PCA reduces the dimension by projecting the data onto a space spanned by the eigenvectors $\vec{v}_i$ with $\lambda_{ii} > T$, where T is a threshold. In other words, the dimension reduction is achieved by ordering the eigenvalues from highest to lowest, to get the components in order of significance. Thus, projecting p eigenvectors that corresponding to highest p eigenvalues, the reduced matrix is defined as:

$$\boldsymbol{S} = \boldsymbol{X}\hat{\boldsymbol{V}} \tag{2}$$

where $\boldsymbol{S} = [s_1, s_2, \ldots, s_p] \in \mathscr{R}^{M\times p}$ is called the score vector or principal component vector and $\hat{\boldsymbol{V}} = [v_1, v_2, \ldots, v_p] \in \mathscr{R}^{N\times p}$ is called the loading vector, are the eigenvectors corresponding to p largest eigenvalues.

Thus, one needs to obtain the eigenvalues $\lambda_{11} > \lambda_{22} > \ldots > \lambda_{NN}$ and plot $f(p) = \sum_{i=1}^{p}\lambda_i / \sum_{i=1}^{N}\lambda_i$, to see how $f(p)$ increases with p and takes the maximum value of i at $p = N$. PCA is good if $f(p)$ asymptotes rapidly to 1. This happens, if the first eigenvalue is big and the remainder are small. PCA is bad if all the eigenvalues are roughly equal.

The data reconstruction can be done by:

$$\overline{\boldsymbol{X}} = \boldsymbol{X}\hat{\boldsymbol{V}}\hat{\boldsymbol{V}}^T \tag{3}$$

Therefore, the data matrix $\boldsymbol{X}$ can be written as:

$$\boldsymbol{X} = \overline{\boldsymbol{X}} + \boldsymbol{E} = \boldsymbol{X}\hat{\boldsymbol{V}}\hat{\boldsymbol{V}}^T + \boldsymbol{X}(I - \hat{\boldsymbol{V}}\hat{\boldsymbol{V}}^T) \tag{4}$$