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Robust signal reconstruction for condition monitoring of industrial components via a modified Auto Associative Kernel Regression method

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ABSTRACT

In this work, we propose a modification of the traditional Auto Associative Kernel Regression (AAKR) method which enhances the signal reconstruction robustness, i.e., the capability of reconstructing abnormal signals to the values expected in normal conditions. The modification is based on the definition of a new procedure for the computation of the similarity between the present measurements and the historical patterns used to perform the signal reconstructions. The underlying conjecture for this is that malfunctions causing variations of a small number of signals are more frequent than those causing variations of a large number of signals. The proposed method has been applied to real normal condition data collected in an industrial plant for energy production. Its performance has been verified considering synthetic and real malfunctioning. The obtained results show an improvement in the early detection of abnormal conditions and the correct identification of the signals responsible of triggering the detection.

1. Introduction

Condition monitoring is used to assess the health state of industrial components and identify possible incipient faults [38,35,26,41]. For this, a model is usually built to reconstruct the values of the monitored signals expected in normal conditions of the components [19]. During operation, observed signal measurements are compared with the reconstructions provided by the model: abnormal components conditions are detected when the reconstructions are remarkably different from the measurements. Data-driven (empirical) models are employed in those cases in which analytical models of the component behavior are not available and cannot be easily developed, whereas historical data collected during operation are available and limited number of hypotheses are required for building a data-driven model [39,40,22].

Reconstruction methods are used in very different sectors, ranging from missing data reconstruction with various applications such as seismic data [14,30], genetics [27,7], climatology [18], to financial applications, image analysis [9,10] and condition monitoring of industrial components [17,15,34,25,20,12,28,1,2,5].

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With respect to condition monitoring of industrial components, several methods have been shown to provide accurate reconstructions of the measured signals under normal operations. However, it has been noticed that these methods tend to suffer of high computational costs [23] and to be not robust [3]. By robustness, here we intend the property that in case of abnormal conditions the reconstructions of the signals are properly estimating the values of the signals expected in normal conditions of the components [1]. In particular, it has been shown that, especially when the measured signals are highly correlated, the reconstruction provided by AutoAssociative Kernel Regression (AAKR) method [1] of an anomalous transient characterized by a drift of one signal can be not satisfactory for two reasons: (1) the reconstruction of the signal affected by the drift tends to assume values in the middle between the drifted and the expected values of the signal in normal conditions; (2) the reconstructions of other signals not affected by the drift tend, erroneously, to be different from the signal measurements, (this latter effect is usually referred to with the term ‘spill-over’). The consequence of (1) is a delay in the detection of abnormal conditions, whereas the consequence of (2) is that the condition monitoring system, although it correctly triggers an abnormal condition alarm, it is not able to correctly identify the signal that triggers the alarm.

These limitations of reconstruction models have been already studied in [12,1]. Solutions to these problems have been proposed, which amount to try to exclude the signals with abnormal behaviors from the set of input signals used to perform the reconstruction. In [2,3,13], the authors have propounded ensembles of reconstruction models handling different sets of input signals. In case of an anomaly impacting the behavior of a generic signal, only the few models fed by that signal provide non-robust reconstructions, whereas all the other models provide correct reconstructions. Conversely, in [4], an ensemble of different reconstruction models handling the same set of input signals is proposed. Another solution has been embraced in [16], whereby a ponderation matrix iteratively modifies its elements to reduce the contribution of abnormal signals to the reconstruction but the convergence of the method to correct signal reconstructions has not been yet demonstrated and all these solutions come at high computational costs.

The objective of the present work is to propose a robust signal reconstruction method with low computational cost and (i) capable of early detection of abnormal conditions, (ii) accurate in the reconstructions of the values of the signals impacted by the abnormal conditions and (iii) resistant to the spill-over effect.

The proposed method is based on the modification of the measure of similarity used by the AAKR method: instead of measures of similarity based on Euclidean or Mahalanobis distances, the proposed method introduces a penalty vector which reduces the contribution provided by those signals which are expected to be impacted by the abnormal conditions. The rationale behind this proposition of the modification is the attempt to privilege those abnormal conditions caused by the most frequently expected malfunctions and failures. The performance of the proposed method has been verified considering (i) synthetic malfunctioning simulated on real healthy data and (ii) real abnormal conditions collected from an industrial plant for energy production [5]. The remainder of the paper is organized as follows. In Section 2, the fault detection problem is introduced. In Section 3, the AAKR method is briefly recalled. Section 4 shows the limitation of the traditional AAKR approach to condition monitoring and states the objectives of the present work. In Section 5, the proposed modification of the traditional AAKR is described and discussed. In Section 6, the application of the proposed method to a real case study concerning the monitoring of 6 signals in an industrial plant for energy production is presented. Finally, in Section 7 some conclusions are drawn.

2. Fault detection

We consider condition monitoring scheme for fault detection as shown in Fig. 1. The (empirical) model reproducing the plant behavior in normal conditions receives in input the vector, $\overrightarrow{x}^{obs}(t)$, containing the actual observations of the J signals monitored at the present time, t, and produces in output the reconstructions, $\hat{\overrightarrow{x}}_{nc}(t)$, i.e. the values that the signals are expected to have in normal conditions [3]. If the actual conditions at the time t are instead, the residuals $\Delta\overrightarrow{x} = \overrightarrow{x}^{obs}(t) - \hat{\overrightarrow{x}}_{nc}(t)$, i.e. the variations between the observations and the reconstructions, are larger and can be detected by exceedance of a prefixed thresholds by at least one signal.

3. Auto Associative Kernel Regression (AAKR)

Different empirical modeling techniques have been applied to the problem of signal reconstruction, such as AutoAssociative Kernel Regression (AAKR) [21,2], Principal Component Analysis (PCA) [15,20], Robust Principal Component Analysis [24], Fault-relevant PCA (FPCA) [44], Partial Least Squares (PLS) [32], Evolving Clustering Method (ECM) [45], Parzen Estimation [28,11], fuzzy-logic-based systems [31], AutoAssociative (AA) and Recurrent (R) Neural Networks (NN)

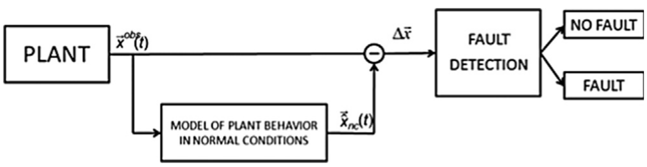

Fig. 1. Scheme of condition monitoring for fault detection.