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Kullback-Leibler Divergence for fault estimation and isolation : Application to Gamma distributed data

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A B S T R A C T

In this paper we develop a fault detection, isolation and estimation method based on data-driven approach. Data-driven methods are effective for feature extraction and feature analysis using statistical techniques. In the proposal, the Principal Component Analysis (PCA) method is used to extract the features and to reduce the data dimension. Then, the Kullback-Leibler Divergence (KLD) is used to detect the fault occurrence by comparing the Probability Density Function of the latent scores. To estimate the fault amplitude in case of Gamma distributed data, we have developed an analytical model that links the KLD to the fault severity, including the environmental noise conditions. In the Principal Component Analysis framework, the proposed model of the KLD has been analysed and compared to an estimated value of the KLD using the Monte-Carlo estimator. The results show that for incipient faults (<10%) in usual noise conditions (SNR > 40 dB), the fault amplitude estimation is accurate enough with a relative error less than 1%. The proposed approach is experimentally verified with vibration signals used for monitoring bearings in electrical machines.

1. Introduction

Fault detection and diagnosis has received increasing attention since the last two decades. The detection of faults at an early stage, their isolation and the analysis of their causes are essential to ensure the safety, reliability and good performances of the application.

For example, electrical rotating machines usually operate by means of bearings which are among the most critical components [1]. The quality of the motor system operation is closely related to the performance of bearing assembly. Among the state-of-the-art, vibration monitoring is asserted to be one of the most effective and practical techniques to detect and diagnose bearing faults [2–5]. Although bearing vibration signals, which cover displacement, velocity and acceleration signals, are rarely straightforward and may contain vibration components generated by various mechanical and electromagnetic forces, they provide the most salient information for the early detection of bearing faults. Unfortunately, the vibration sensors may be exposed to failures in hard industrial conditions. Therefore, it is necessary to detect these failures and to estimate their amplitudes in order to correct the measurements.

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Nomenclature

CWRU	Case Western Reserve University
FDD	Fault Detection and Diagnosis
FNR	Fault to Noise Ratio
hp	Horse Power
KLD	Kullback-Leibler Divergence
KLI	Kullback-Leibler Information
MC	Monte Carlo
MLE	Maximum Likelihood Estimate
MMSE	Minimum Mean Square Estimation
PCA	Principal Component Analysis
PDF	Probability Density Function
rpm	round per minute
SNR	Signal to Noise Ratio
SPE	Squared Prediction Error

Just as any dynamic system, a sensor fails if a failure occurs in any of its components including the sensing device, transducer, signal processor, or data acquisition equipment. An abrupt failure in the sensor can be caused by a power failure or corroded contacts, while an incipient failure such as drift and precision degradation can be caused by deterioration in the sensing element. As defined in [6,7], both an abrupt and an incipient failure can cause non-permitted deviation from the characteristic property in a sensor, which leads to inaccurate measurements from the monitored system. Consequently, a faulty sensor can cause process performance degradation, process shut down, or even worse in a safety critical system. In fact, the problem of instrument fault detection, identification and accommodation has already received extensive attention in both industrial and academic fields [8–12]. Nevertheless, the detection of incipient sensor failures that is important for critical information to diagnose and control systems has received limited attention in literature [13].

A conventional engineering method for sensor validation is to check and recalibrate a sensor periodically according to a set of predetermined procedures [14]. Although this method has been widely implemented in industry for detecting abrupt sensor failures, it is not able to accomplish continuous assessment of a sensor, and thus is not effective in detecting its incipient failure. Moreover, due to their ever increasing number, it has become cost ineffective and even infeasible to check all sensors periodically. Therefore, significant efforts have been made for the development of more systematic methods, which can be generally categorized into hardware and analytical redundancy approaches [15]. The general idea of the hardware redundancy approaches is to measure one critical variable using two or more sensors, and then detect as well as isolate the faulty sensor by consistency checking and majority voting. These approaches have been widely used in safety-critical systems for their simplicity and robustness. Without the use of additional sensors, the analytical redundancy approaches identify the functional relations between the measured variables via a mathematical model that can be either developed based on the underlying physics or derived directly from the measurements. Residuals between the sensor measurements and the modeled outputs can then be generated for the detection and isolation of the faulty sensor. The methods developed in this framework can be classified into three main categories: quantitative model-based, qualitative model-based and process history based or so-called data-driven approach [16–19].

Different from model-based approaches that require accurate analytical multiphysics-based description of the target system, data-driven methods, also known as process history based methods, require the availability of sufficient data. Various methods have been developed to establish the knowledge database for the underlying system by extracting characteristic features directly from its past performance data. We can find in this approach different methods like multivariate statistical methods [20], Bayesian belief networks [21], and neural networks [22].

In this paper, we adopt a data-driven approach [23] using descriptive features within the Principal Component Analysis (PCA) [24–26] framework combined with multivariate statistical techniques to develop an efficient fault detection and estimation method.

PCA-based monitoring methods can easily handle high dimensional, noisy and highly correlated data generated from industrial processes, and provide superior performance compared to univariate methods [24]. In addition, these process monitoring techniques are attractive for industrial practical processes because they only require a good historical data set of healthy operation, which are easily obtainable for computer-controlled industrial processes. PCA-based monitoring methods and their extensions have been successfully applied in a wide range of applications and industries, such as in chemical processes, air quality, water treatment, aerospace, agriculture, automotive, electronics, energy, manufacturing, medical devices, and many others [27].