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Process fault detection based on dynamic kernel slow feature analysis ☆

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ABSTRACT

A fault detection method based on dynamic kernel slow feature analysis (DKSFA) is presented in the paper. SFA is a new feature extraction technology which can find a group of slowly varying feature outputs from the high-dimensional inputs. In order to analyze the nonlinear dynamic characteristics of the process data, DKSFA is presented which applies the augmented matrix to consider the dynamic characteristic and uses kernel slow feature analysis (KSFA) to extract the nonlinear slow features hidden in the observed data. For the purpose of fault detection, the D monitoring statistic index is built based on DKSFA model and its confidence limit is computed by kernel density estimation. Simulations on a nonlinear system and Tennessee Eastman (TE) benchmark process show that the proposed method has a better fault detection performance compared with the conventional (kernel principal component analysis) KPCA-based method.

1. Introduction

Process monitoring is very important to ensure safe operation and production of high quality products in the industrial production process. Once a fault happens, enormous economic loss may be made, even it can cause casualty and pollute the environment severely. Data-driven methods have gained great attention and become a research hotspot gradually in the fields of fault diagnosis in recent years. However, the high-dimensional data often include some redundant information and the key point of data-driven methods is to extract the feature information from multi-dimensional measured signals [1–4].

Multi-variable statistical process monitoring technology such as principal component analysis (PCA) [5], partial least squares (PLS) [6], and independent component analysis (ICA) [7,8], have been used widely and successfully in the research fields. However, these methods mentioned above are the linear dimensional reduction techniques which may cause incorrect results for nonlinear industrial process. Besides, nonlinear transformations aiming to the original variables are not easy to construct. To address the nonlinear characteristics of the process, several nonlinear extensions of the traditional PCA method have already been proposed such as principle curves [9] and neural network [10–12]. Lawrence proposed Gaussian process latent variable model (GP-LVM)[13] which could easily be non-linearized through Gaussian processes, and related to popular spectral techniques. Recently, nonlinear process monitoring methods based on kernel function were proposed [14–17], which have been applied for fault detection and fault diagnosis successfully. Kernel PCA (KPCA) [18,19] firstly

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mapped the inputs into a linear feature space by a nonlinear mapping, and then extracted principal components in the kernel feature space.

Slow feature analysis (SFA), a new learning principle, is inspired by slow change phenomenon that occurs in real life. SFA aims for invariant features out of the high-dimensional measurements. It can extract the slowly varying features which carry significant information. The obtained feature components are mutually uncorrelated and independent from each other. SFA differs from simple low-pass filter fundamentally. If the input signals have some underlying and slowly varying causes, SFA can always extract slowly varying output signals. Through SFA algorithm [20], we can obtain the slowly varying features which are very useful for classification and identification from input signals. Berkes and Wiskott employed it to learn the self-organized receptive field of cortical neuron from synthetic image sequences [21,22]. Zhang considered four kinds of SFA learning strategies to extract slow feature functions from a large amount of training cuboids for human action recognition [23]. MA proposed kernel-based method to solve the nonlinear expansion problem of SFA and supplied an algorithm evaluation criterion [24]. All the above findings suggest that SFA can extract the useful slow feature information for data analysis.

In this paper, a nonlinear dynamic fault detection method is introduced based on dynamic kernel slow feature analysis (DKSFA), which can generate a set of output signals that vary as slowly as possible but carry significant information from the input signals. The monitoring statistic index is constructed for process monitoring with the extracted information. The effectiveness of the proposed method is demonstrated through a numerical sample and Tennessee Eastman (TE) process. The following sections sketch the introduction of the algorithm and its application. Firstly, the SFA algorithm is reviewed in Section 2, as it is necessary for understanding the remainder of the work. The nonlinear dynamic fault detection method named DKSFA is also presented in Section 2. Section 3 describes the procedure of the fault detection method based on DKSFA. Simulation studies on a simple nonlinear system and the TE process are shown in Section 4, followed by a discussion of the proposed method in Section 5.

2. Dynamic kernel slow feature analysis algorithm

2.1. Slow feature analysis

Given a multi-dimensional input signal $\boldsymbol{x}(t)$, SFA algorithm can find a set of function, and the output signals $y_j(t) = f_j(\boldsymbol{x}(t))$ can be generated through f_j. SFA focuses on finding slowly varying components from the input signals.

Let $\boldsymbol{x}(t) = [x_1(t), x_2(t), \ldots, x_m(t)]^T$ be the m-dimensional input signals, $\boldsymbol{y}(t) = [y_1(t), y_2(t), \ldots y_{m_1}(t)]^T$ be the m_1-dimensional output signals, and $\boldsymbol{f}(x) = [f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_{m_1}(\boldsymbol{x})]^T$ be a set of real valued functions. The primary objective of SFA is as follows:

$$\min \Delta y_j(t) = \langle \dot{y}_j^2 \rangle_t \tag{1}$$

under the constraints of

$$\langle y_j \rangle_t = 0 \tag{2}$$

$$\langle y_j^2 \rangle_t = 1 \tag{3}$$

and

$$\forall i < j, \langle y_i y_j \rangle_t = 0 \tag{4}$$

where $\dot{y}$ denotes the first order derivative of y and $\langle \cdot \rangle_t$ is the mean of signal y over time. Eq. (1) introduces the temporal variation measure of the output signals, which is equal to the mean of the squared first order derivative of the original measured signals. Its value is large for quickly varying signals and is close to zero for lower varying signals. The zero mean constraint (2) is introduced for convenience. Constraint (3) means that the transformed output signals should carry some information and prevent constant signals $y_j(t) = const$ from emerging. Different output components carry different aspects of information, and they can reflect different characteristics of input information. Besides, it also induces an order [21]. The first output signal is the slowest one, and the second is the second slowest while obeying the constraint (4), etc.

2.2. Kernel slow feature analysis

The nonlinear mapping relationship between input data and output data is:

$$\boldsymbol{y}(t) = \psi(\boldsymbol{x}(t)) \tag{5}$$

However, it is not easy to obtain the implicit mapping ψ directly. Therefore, the idea of KPCA is introduced to extend SFA for extracting nonlinear slow features in the paper.