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An unsupervised feature extraction method for nonlinear deterioration process of complex equipment under multi dimensional no-label signals

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ABSTRACT

The nonlinearity in complex equipment, such as turbofan engine and electric motor, is a substantial factor. The nature of complex equipment deterioration refers to a nonlinear deterioration process. An unsupervised feature extraction method based on greedy kernel principal components analysis (GKPCA) is proposed for nonlinear deterioration process under multi dimensional no-label signals. The 21 signals of turbofan engine and 6 signals of electric motor are analyzed using the method, respectively. The results show that: taking the first component as deterioration feature of complex equipment in system-level is appropriate; the more exact deterioration features with better performance in monotonicity, robustness and computation speed, are identified from GKPCA-PC1, thus the features can be used for online monitoring and warning of complex equipment; the unsupervised feature extraction method considering nonlinearity is more effective and efficiency for deterioration level identification and health management such as adding lubricant grease at optical time to prevent Over-alarm. The results verify the effectiveness and efficiency of the method in dealing with nonlinearity in deterioration feature extraction of complex equipment. Through the study, it reveals that considering the substantial nonlinearity in complex equipment is important for extracting more exact deterioration feature under multi dimensional no-label signals.

1. Introduction

In recent years, prognostics and health management (PHM) has revolutionized the perception of industrial systems reliability and has attracted many scholars. Deterioration feature extraction, as the fundamental condition of PHM, was crucial for deterioration modeling and RUL prediction [1]. Deterioration data, in which the failure mode, position and degree of equipment are not known practically, are multi dimensional no-label signals. In order to reveal the deterioration feature of equipment, unsupervised feature extraction was necessary indeed. Recently, many researchers were interested and paid attention on unsupervised feature extraction under multi dimensional no-label signals.

A principal components analysis (PCA) based unsupervised feature extraction method for crack detection of high-speed rotating blades was presented by Chen et al. [2]. A PCA based feature extraction method was proposed for robot interaction events identification using multi sensors by Mazzei et al. [3]. In order to differentiate the target gas sources, monitoring data from sensor array were analyzed using PCA to extract the feature by Su et al. [4]. An improved fisher discriminant analysis based supervised feature extraction method for fault detection in bearing and gearbox was proposed by McBain et al. [5]. An unsupervised feature extraction method based on PCA was proposed by Kuncheva et al. to apply for feature extraction prior to change detection in multi unlabeled data [6]. A PCA based fault diagnosis method was proposed for automaton by Cao et al., the extracted feature vector could discard the redundant information and accurately describe the fault [7]. A PCA based method is proposed for feature reduction so as to correlation decrease in vibration analysis of nondestructive diagnosis system by Su et al. [8]. The PCA procedure was employed and kernel trick was adopted to map the nonlinear data into a feature space by Widodo et al., and they were applied to classify the faults of induction motor [9]. The PCA and kernel PCA (KPCA) were used for unsupervised fault feature extraction and classification of gear by Shao et al. [10]. A feature extraction method based on KPCA for discrimination of indoor air contaminants with multi sensors by Peng et al. [11]. The deterioration feature extracted from multi sig-

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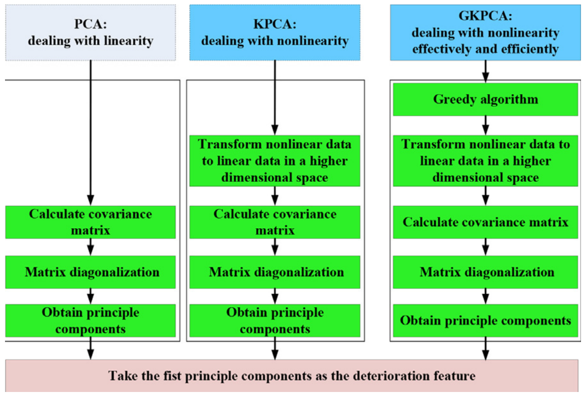

Fig. 1. The procedure of three unsupervised feature extraction methods.

nals was employed to characterize the health state of deterioration process and estimate the parameters of deterioration model by Sun et al. [12]. A practical framework and significant progress in deterioration modeling was achieved by Moghaddass, due to focusing on the deterioration modeling, the linearity assumption was adopted, and an unsupervised linear algorithm called PCA was employed to extract the deterioration feature from 21 dimensional no-label signals, and then the feature was used for deterioration modeling and RUL prediction [13]. Most researchers paid much attention and made thorough progress in unsupervised feature extraction for components and complex equipment, but they primarily focus on the short-term fault feature extraction, and individual researcher paid attention on the long-term deterioration feature extraction of complex equipment under linear assumption.

Actually, the nonlinearity in complex equipment, such as turbofan engine and electric motor, is a substantial factor [14]. The nature of complex equipment deterioration refers to a nonlinear deterioration process, where the deterioration curve (drawn w.r.t. time) may not follow a typical shape such as exponential or linear function [15]. The deterioration features of complex equipment are always a direct result of the nonlinearity [16,17], but few researcher takes a systemic consideration on feature extraction of nonlinear deterioration process under multi dimensional no-label signals. The feature extraction of nonlinear deterioration process is one of most important challenges in RUL prediction of complex equipment. In order to overcome the linear assumption that deterioration feature curves follow specific shape such as exponential or linear, and avoid the time consuming nonlinear computation, an unsupervised feature extraction method based on greedy kernel principal components analysis (GKPCA) is proposed to meet the challenge. The proposed method will deal with the nonlinear deterioration process in an effective and efficient manner under multi no-label signals.

The structure of this paper is as follow: Section 2 is Unsupervised feature extraction method for nonlinear deterioration process, Section 3 is Deterioration feature extraction of complex equipment, and Section 4 is Conclusion.

2. Unsupervised feature extraction method for nonlinear deterioration process

Unsupervised feature extraction method for nonlinear deterioration process plays an important role in deterioration modeling of complex equipment. The procedure of feature extraction method studied in this paper is shown in Fig. 1 as follows.

2.1. Unsupervised feature extraction method based on PCA from multi signals

PCA was invented by Pearson as an analogue of the principal axis theorem in mechanics. It is a simple, non-parametric method for extracting relevant information [17] by using a linearly transformation to convert a high-dimensional and possibly correlated data set into a low-dimensional and uncorrelated orthogonal variables called principal components which reveal the hidden, simplified structures under the data set. The transformation is defined by projecting the data set from its most informative viewpoint in such a way that the first principal component has the largest possible variance (includes most useful information), and each succeeding component in turn has the highest variance.

Actually, the m dimension original data set with n time observations can be obtained from measurements of m sensors in engineering system. The centered data set can be recorded as an $m \times n$ matrix X, where each column vector is a sample of the data set with m elements and each row vector is a time series of one sensor with n elements. Let Y be another $m \times n$ matrix as a new representation of X related by a linear transformation P in Eq. (1).

$$\mathrm{PX} = \mathrm{Y} \tag{1}$$

In Eq. (1), a change of basis is represented, and P is a matrix that transforms X into Y. The rows of P, $[p_1, p_2, \ldots\ldots p_{m-1}, p_m]$, are a set of new basis vectors for expressing the columns of X. If x_i ($x_i \in R_m$) is defined as the column of X, y_i is defined as the column of Y, then Eq. (1) can be transformed into Eq. (2).

$$\begin{aligned} Y = PX &= \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_m \end{bmatrix} \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \\ &= \begin{bmatrix} p_1x_1 & p_1x_2 & \cdots & p_1x_n \\ p_2x_1 & p_2x_2 & \cdots & p_2x_n \\ \vdots & \vdots & \vdots & \vdots \\ p_mx_1 & p_mx_2 & \cdots & p_mx_n \end{bmatrix} = \begin{bmatrix} y_1 & y_2 & \cdots & y_n \end{bmatrix} \end{aligned} \tag{2}$$

The covariance matrix of X can be defined as C_X. C_X is a square symmetric $m \times m$ matrix, and each diagonal element of C_X is the variance of a particular sensor data, each non-diagonal element of C_X is the covariance between two different measurements. The covariance values reflect the noise and redundancy in all measurements. In the diagonal elements, by assumption, large values refer to interesting information, and in the non-diagonal elements large values refer to high redundancy.

$$C_X = \frac{1}{n} XX^T \tag{3}$$

The goals of PCA are: (1) to minimize redundancy (the covariance), and (2) maximize the signal (the variance), thus the covariance matrix C_X should be converted to a diagonalizable matrix C_Y by P as follows.

$$C_Y = \frac{1}{n}(PX)(PX)^T = P(\frac{1}{n}XX^T)P^T = PC_XP^T \tag{4}$$

In Eq. (4), P is a $m \times m$ matrix, and C_X can be converted to a diagonalizable matrix D. Make $P = QT$, then $C_Y = D$ as Eq. (5).

$$\begin{aligned} C_Y &= PC_XP^T = P(QDQ^T)P^T \\ &= (PQ)D(PQ)^T = (PP^T)D(PP^T) = D \end{aligned} \tag{5}$$