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Decentralized fault diagnosis using multiblock kernel independent component analysis

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ABSTRACT

In this paper, a multiblock kernel independent component analysis (MBKICA) algorithm is proposed. Then a new fault diagnosis approach based on MBKICA is proposed to monitor large-scale processes. MBKICA has superior fault diagnosis ability since variables are grouped and the non-Gaussianity is considered compared to standard kernel methods. The proposed method is applied to fault detection and diagnosis in the continuous annealing process. The proposed decentralized nonlinear approach effectively captures the nonlinear relationship and non-Gaussianity in the block process variables, and shows superior fault diagnosis ability compared to other methods.

Keywords: Multiblock kernel methods; Process monitoring; Kernel independent component analysis; Fault detection and diagnosis

1. Introduction

With the increasing of the data collection ability and the widely using of the distributed control system (DCS), a large number of data are accumulated in the industrial process. These data contain a wealth of information about process characteristics, which is the solid foundation of the process monitoring and fault diagnosis. Multivariate statistical method such as principal component analysis (PCA) can effectively remove the linear redundant information of the data and get a small number of important variables of the process characteristic (Chiang et al., 2001; Jackson & Mudholkar, 1979; Kresta et al., 1991; Ku et al., 1995; Li et al., 2000; Nomikos & MacGregor, 1995; Lee et al., 2004; Wise and Gallagher, 1996). The multivariate statistical method, which has simple algorithm and is easy to apply, now is widely used in chemical process monitoring and fault diagnosis. However, there are two important assumptions in practical application of PCA, one is that the process data is linear related, which limits the application of PCA in strong nonlinear industrial process, and the other is that the process is time invariant, that is, the linear relationship among the variables does not change with the operation of the process (Chen and McAvoy, 1998; Choi & Lee, 2005; Kourti et al., 1995; MacGregor et al., 1994; Qin, 2003; Qin et al., 2001; Wangen & Kowalski, 1989; Westerhuis & Coenegracht, 1997; Westerhuis et al., 1998).

Now, there are mainly two kinds of approaches to solve the nonlinear process monitoring, one is neural network algorithm, specifically including the five layer neural network method, the principle component curve-neural network method algorithm (Dong & McAvoy, 1996; Mark, 1991; Tan & Mavrovouniotis, 1995), and so on. Because of on the basic of experience risk minimization, there is no guarantee to the generalization ability of the model (Walczak & Massart, 2000). In addition, the structure of the model is difficult to determine, which needs to solve complex nonlinear optimization problem. The other kind is the kernel learning method (Kocsor & Toth, 2004; Mika et al., 1999; Romdhani et al., 1999), such as kernel principle component analysis (KPCA) (Scholkopf et al., 1998, 1999), and so on. The kernel methods map the nonlinear data into the high dimensional feature space, and do the linear operator to extract the feature in that space. Because of on the basic of structure risk minimization, the kernel method can solve the problem of generalization ability better. With the simple computing, the kernel methods have made a lot of application in industrial process monitoring. There are two kinds of disadvantages to the traditional KPCA algorithm. Firstly, KPCA operate the input data set as an entirety,

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