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HSIC-based kernel independent component analysis for fault monitoring

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ABSTRACT

For nonlinear and non-Gaussian industrial processes, KICA is a mature and successful method for fault monitoring. However, a fixed-point ICA algorithm uses a negative entropy method, which has relatively high requirements for non-quadratic function and initial point; accuracy is unsatisfactory. The calculation of control limits of Hotelling's T^2 statistic is based on a kernel density estimation, which is difficult to calculate and implement and sometimes cannot guarantee accuracy. In this paper, the kernel independent component analysis method based on the Hibert-Schmidt independence criterion (HSIC) is used instead of the fixed-point ICA algorithm for fault monitoring to improve the accuracy of the independent element. We obtain the independent element directly from the objective function, rather than through the combination of KPCA and ICA. At the same time, we use the direct binomial expansion theorem to obtain the control limit, which reduces computational complexity and implementation difficulty and improves accuracy. The control limit is improved to obtain multi-fault diagnosis. Gray-level information and color information of each frame of the video are respectively read through the information entropy and HSV spatial color histogram. Experimental results show the advantage and effectiveness of the proposed approach. Meanwhile, shadow variables are introduced to smooth the statistics. The contributions of this paper are as follows. 1) Using the kernel independent component method based on HSIC for fault monitoring improves speed and accuracy. 2) The binomial expansion theorem is used instead of traditional kernel density estimation to calculate the control limit, which improves the results of fault monitoring. 3) A method of fault detection using information entropy, HSV color histogram and multivariate statistical analysis is presented.

1. Introduction

With the development of modern industrial processes, complexity is increasing. The equipment structure and composition of modern industry is complex, and the scale of production is very large; the links between departments are particularly close [1]. Loss of time due to equipment faults and downtime increases rapidly [2,3]. In the event a fault stops production, it will often cause huge economic losses and even catastrophic consequences.

However, it is unrealistic to expect the equipment to run normally all the time. It is important to timely detect equipment anomalies and faults, understand the operational status of the equipment, grasp its development trend, determine the location of the fault and the causes, and take early and effective prevention and control measures.

With the growth of computer systems and database systems, the factory has a wealth of production data resources, which provide data assurance for the application of multivariate statistical methods [4]. By using multivariate statistical methods to analyze the production data and reveal changes in the production process can provide useful information for understanding the state of production, thereby translating a single data resource into useful information that reflects the state of production and production quality.

The variables of the study object are interrelated under multivariate statistical process control. When one or more variables of the interrelated statistical indicators deviate from the overall level, the production process has a fault. Research on fault detection methods based on multivariate statistical analysis is developing continuously. Several fault detection methods have been developed and have been applied to actual production process monitoring. Independent component analysis (ICA) is one of such fault detection methods [5]. ICA is a signal processing method developed in the field of signal processing in 1990. It is a new blind source BBS technique, that is, in the case of only knowing the mixed signal, separate from the source signals. In 1994, Comon [6] systematically expounded the concept of independent meta-analysis and gave a strict mathematical definition. It is clear that an independent source signal with at most one Gaussian component can be expressed by a

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function called a contrast function. The objective function of the contrast function reaches a maximum value to eliminate the high-order statistical correlation in an observed signal to realize the blind separation of the signal. In this way, the independent component analysis of the random vector can be transformed into an optimization problem. In the mid-1990s, Bell and Sejnowski [7] proposed a new ICA algorithm based on the principle of information maximization, and the ICA algorithm was widely used. Compared with the traditional statistical control method, correlation of the variables is eliminated, and the high-order statistical properties are obtained to get more useful information.

From the central limit theorem, we know that the mixed signal of multiple independent variables approaches a Gaussian distribution. Thus, Hyvărinen et al. proved that independence is equivalent to Gaussianity theoretically, which makes it possible to quantify the independence of measurement [8]. Thus, ICA transforms independent variables to maximize non-Gaussianity.

At present, there are many algorithms for obtaining independent elements, but the most representative algorithm is the FastICA algorithm proposed by Finnish scholar Hyvărinen et al. [9,10]. The algorithm belongs to the batch algorithm, which uses block learning to adjust the separation matrix coefficient. It has fast convergence, does not need to learn step size parameters, and does not need the requirements of independent variables to extract. Many scholars have demonstrated the simulation and confirmation of FastICA's convergence speed and stability. However, the FastICA algorithm has several shortcomings: a) the negative entropy measurement method is an approximate measurement method and cannot accurately reflect the independence of the calculated variables; b) whether the negative entropy is better depends on the choice of non-quadratic function; and c) if the choice of the initial value of the algorithm is not appropriate, the algorithm may not converge, causing inaccurate independent element calculation.

In the early 1990s, ICA's application was limited. The ICA algorithm was mainly used in speech signal processing, which was a very effective method for dealing with non-Gaussian signals [11]. Because ICA decomposes the observed data into a linear combination of statistically independent principal components, it can extract parts of non-Gaussian measurements, and it is suitable for fault monitoring and diagnosis. The ICA method was introduced into the fault monitoring field. Kano et al. first applied the ICA method to the field of fault monitoring and proposed a process monitoring method based on ICA [12]. Subsequently, Lee proposed new monitoring indicators using the ICA framework: T^2, T_e^2 and *SPE* [13]. However, due to the linearity of the ICA, they cannot be effectively independent of nonlinear data; therefore, the monitoring results in the nonlinear process are not ideal. To solve the problem of nonlinearity of the data, some nonlinear multivariate statistical analysis methods have been developed. However, most nonlinear methods proposed are based on a neural network algorithm [14]. How to calculate the principal component is urgent. Solving the nonlinear optimization problem and before training the neural network, the number of PCs must be cleared and ensured. Considering the nonlinear nature of industrial processes, Lee J M proposed a nonlinear monitoring technique based on kernel methods, called KPCA [15]. This can effectively monitor a nonlinear continuous process and does not involve nonlinear optimization compared to other nonlinear methods. The number of principal components does not need to be specified before modeling [16], showing its powerful advantage. Lee et al. [17–20] proposed a KICA algorithm to solve fault monitoring and diagnosis of nonlinear processes, and KICA-based face recognition had good results [21]. Qin and Zhang et al. proposed a kernel ICA-based fault diagnosis method for the introduction of nonlinear process data into the kernel method [22].

KICA can be divided into two parts: KPCA and ICA. First, data mapped to higher dimensions need to be whitened and reduced to obtain unrelated whitening data. Then, ICA is called to extract the nonlinear independent components. Ge et al. proposed the combination of PCA and ICA to establish a combined process monitoring method [24]. For ICA, PCA can be imitated, and the actual process can be monitored based on the statistical method. Since the number of independent elements obtained by the ICA algorithm is equal to the number of original data variables and cannot be as significant as the PCA, it is not convenient to choose representative data such as PCA information of the "independent main element". In response to this problem, Lee and Qin proposed a strategy: first, PCA processing data obtains a few PCs, as IC initial estimates; then, the FastICA algorithm is used to update ICs and ICA to meet the independence requirements [23]. This is bound to increase the amount of computation. Lee and Yoo proposed another way: use the ICA algorithm to obtain all the independent elements and transformation matrix directly; calculate the matrix of each vector norm L_2, follow the large and small re-arranged [24,25], and then select the PCA ICs in accordance with the importance of descending order. Fortunately, HSIC [26] does not assume a data distribution and can measure the strength of independence between the estimated pairs of independent components. Based on the above analysis, it is better to use this method to calculate the independent element for process monitoring.

The rest of this paper is organized as follows. In the second part, we review the relevant knowledge. In the third part, we optimize the established objective function to obtain independent elements. The fourth part uses the required independent element for fault detection and a new method to obtain the control limit and apply it to multiple fault diagnosis. The simulation results are shown in section five. Finally, the conclusion is presented in the sixth part.

2. Preliminaries: ICA for fault monitoring and HSIC

2.1. ICA for fault monitoring

Suppose that there is an observational variable $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_\mathbf{d}$, which can be a linear combination shown by non-Gaussian independent component $\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_\mathbf{m} (m \le d)$. When the independent component analysis is carried out, it is necessary to center and whiten the original data, so that each variable can be transformed into the mean value of 0 and the variance of 1. The resulting random variables are $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_\mathbf{d}]^T$ and $\mathbf{s} = [\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_\mathbf{m}]$, respectively; assuming there is no noise or low additive noise, the following relationship exists between them:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

Where $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, L\mathbf{a}_\mathbf{m}] \in \mathbf{R}^{d \times m}$ is an unknown mixing matrix. The core problem of the independent element analysis algorithm is to estimate the hybrid matrix **A** and independent element **s** only by observing the observation data. This problem is equivalent to estimating the mismatch matrix by which independent source variables can be obtained from the observed variables:

$$\hat{\mathbf{s}} = \mathrm{Wx} \tag{2}$$

Where $\hat{\mathbf{s}}$ is the estimated vector of **s**; when **W** is the inverse of **A**, $\hat{\mathbf{s}}$ is the best estimate of the source variable. Our task is to solve the mixed matrix **W**.

First, let z be the whitening vector of the observed data x and perform a singular value decomposition of the covariance matrix of x:

$$\mathbf{z} = \mathbf{\Lambda}^{-1/2}\mathbf{U}^\mathbf{T}\mathbf{x} = \mathbf{Q}\mathbf{x} \tag{3}$$

Then,

$$\mathbf{z} = \mathbf{Q}\mathbf{x} = \mathbf{Q}\mathbf{A}\mathbf{s} = \mathbf{B}\mathbf{s} \tag{4}$$

Because $\mathrm{E}\{z\mathbf{z}^\mathbf{T}\} = BE(s\mathbf{s}^\mathbf{T})\mathbf{B}^\mathbf{T} = B\mathbf{B}^\mathbf{T} = I$, $\mathbf{B} = QA$ is an orthogonal matrix. In this case, the expression for the source signal is

$$\mathbf{Y} = \mathbf{B}^\mathbf{T}\mathbf{z} = \mathbf{B}^\mathbf{T}\mathbf{Q}\mathbf{x} \tag{5}$$