Research Article

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Research on fault detection and identification methods of nonlinear dynamic process based on ICA

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Abstract: In the present study, nonlinear dynamic process data are mapped into the kernel state space by kernel gauge variable analysis method to obtain decorrelated state data. The time-lapse covariance matrix of the state data is weighted and summed to obtain the time-lapse structure matrix of the state data, and then supervised kernel independent component analysis (SKICA) is established, the independent component feature data is extracted from the status data and the monitoring statistics are constructed to detect the process faults. The data show that kernel independent component analysis (KICA) method (KICA) method can detect slow fault faster than the ICA method, except that the statistical detection ability of F3 and FS is reduced, and the KICA method can significantly improve the detection performance of other faults and statistics. By analyzing the detection results of SKICA method, it is obvious that in the detection process of all five kinds of slow faults, the fault detection capability of SKICA is better than that of ICA and KICA. The results of continuous stirred reactor simulation system show that, compared with the basic linear process, the slow fault detection has a good monitoring performance, it can detect the small deviation in the process sensitively and give alarm information to the slow fault in time, to improve the fault detection rate.

Keywords: independent component analysis, fault detection, nonlinear dynamics

1 Introduction

With the extensive application of advanced computer measurement and control technology in the modern industrial process, production equipment is developing toward large-scale, integrated, and intelligent direction [1]. On the one hand, large-scale complex industrial systems can effectively improve the production efficiency and fully meet the market demand for products; on the other hand, the system has a large number of components that are prone to failure. If the small failure of a single component is not eliminated in time, it may cause a chain reaction, resulting in abnormal shutdown, or even catastrophic accidents, especially in the oil and petrochemical industry, due to its special working environment and strict operation requirements, any failure may cause irreparable losses. For example, in 2010, BP’s Deepwater Horizon oil rig in the Gulf of Mexico exploded and caught fire after failing to stop the blowout, causing serious human casualties, environmental damage, and economic losses. Domestic Shengli oil field suffers great economic loss due to pipeline leakage every year. More and more problems of production, safety, and economic benefits require timely and accurate fault detection and diagnosis to ensure safe and efficient operation of industrial systems [2,3]. The complexity of the production process data often exhibit strong nonlinear and dynamic at the same time. Therefore, SKICA method can better meet the needs of the process monitoring but cannot guarantee the accuracy of the extracted principal component which can reflect the dynamic characteristics of the process data [4–6] (Figure 1).

2 Literature review

In view of the nonlinear and dynamic characteristics of industrial processes, Ni et al. proposed a fault detection method, SKICA, based on nuclear state space independent element analysis [7]. Shang et al. found that compared with the traditional fault detection method based
on dynamic kernel principal component analysis (PCA), this method can detect the occurrence of faults more sensitively and improve the fault detection rate [8]. In recent years, fault detection and diagnosis of data-driven processes has become a hot topic in academia and industry. Cai and Tian, proposed that statistical analysis is a data-driven method with many studies and wide attention from researchers [9]. Shi et al. believed that the reason was that actual industrial process variables were usually closely correlated. Multivariate statistical analysis, such as PCA, partial least squares (PLS), independent meta-analysis (ICA), etc., could consider the statistical correlation information between process variables and extract characteristic variables for fault detection and diagnosis [10]. It is worth noting that Dou et al. study is different from PCA, PLS, and other multivariate statistical analysis methods that only consider zero-time-delay second-order information to extract Gaussian features [11]. Du et al. believed that ICA could extract non-Gaussian features by considering high-order information, or simultaneously extract Gaussian and non-Gaussian features by considering second-order time information [12]. According to Shokry et al., as characteristic variables of industrial processes tend to follow non-Gaussian distribution, or some follow Gaussian distribution, some follow non-Gaussian distribution, ICA can extract process features more essentially than other multivariate statistical analysis methods [13]. In many cases, Rui suggests that the collected industrial process data may have complex characteristics, such as outliers, measurement noise, or nonlinear structure, etc., but the current ICA method is not fully considered and cannot obtain effective and reliable feature extraction results [14]. Therefore, combined with the characteristics of industrial process data, targeted algorithm research is carried out around SKICA method in ICA theory, and a set of process fault detection and diagnosis methods based on SKICA are established to enrich and develop ICA theory; it is of great theoretical significance and application value to meet the requirements of fault detection and diagnosis under complex industrial process data [15,16].

3 Methods

3.1 Nonlinear ICA method: Kernel ICA (KICA)

The basic idea of ICA is to conduct blind source separation of multichannel observation signals to obtain mutually independent source signals, which is essentially a linear transformation method [7]. To establish the nonlinear ICA model, the observed data $x$ is mapped to the linear space through the nonlinear transformation, and the data $y$ of the linear relationship is obtained, and then linear ICA analysis was applied to extract the independent elements to
establish the overall nonlinear ICA model [17]. For the thousand observation vectors, assuming nonlinear mapping, little \( \phi(\cdot) \) maps the data to a high-dimensional linear space \( Fy = \phi(x) \), where \( y \) is regarded as the normalized data. In ICA method, \( y \) needs to be automatized first, that is, to find the automatized transformation matrix \( Q \) to make \( z = Qy \) satisfy Eq. (1).

\[
E[zz^T] = 1.
\]  
(1)

The calculation of the automatized transformation matrix \( Q \) is shown in Eq. (2).

\[
Q = \Lambda^{1/2}U^T.
\]  
(2)

Type \( \Lambda = \text{diag}(\lambda_1, \lambda_2, \ldots) \), \( U = [u_1, u_2, \ldots] \), \( \lambda_i, u_i \) is the eigenvalue and eigenvector of the covariance matrix \( R_y \), as shown in Eq. (3).

\[
R_y = E[yy^T] = U\Lambda U^T.
\]  
(3)

As the nonlinear mapping function \( \phi(\cdot) \) is often unknown, the covariance matrix on the left side of Eq. (3) cannot be obtained directly; hence, \( \Lambda, U \) cannot be calculated. Kernel function technology is used to solve the nonlinear mapping problem, let \( X, Y \) respectively, represent the observation matrix composed of \( n \) observation samples of \( x \) and \( y \), then the covariance matrix of \( Y \) is shown in Eq. (4).

\[
R_y = \frac{1}{n-1} YY^T = \frac{1}{n-1} \phi(X)\phi(X)^T.
\]  
(4)

The eigenvalue decomposition of \( R_y \) is performed, as shown in Eq. (5).

\[
R_yu_i = \lambda_iu_i.
\]  
(5)

The eigenvector \( u_i \) is in the span of \( \phi(x_i)(j = 1, \ldots, n) \), so Eq. (6) holds.

\[
u_i = \phi(x)u_i = \sum_{j=1}^{n} u_j \phi(x_j).
\]  
(6)

Eqs. (4) and (6) are substituted into Eq. (5) and then multiplied both sides by \( \phi(x)^T \), as shown in Eq. (7).

\[
\frac{1}{n-1} \phi(x)^T \phi(X)\phi(x)^T \phi(x)u_i = \lambda_i \phi(x)^T \phi(x)u_i.
\]  
(7)

Therefore, the kernel function is defined by applying the kernel function technique to Eq. (7) \( k(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle \), the meaning of kernel function is to calculate the innermost product of the nonlinear transformation with the kernel function of the vector in the original space [18]. The existing literature provides a variety of kernels for selection, using polynomial kernels, for the observation data matrix \( X \), there are \( \phi(x)^T \phi(x) = K \), among them \( [K]_{ij} = k(x_i, x_j) \). Therefore, Eq. (7) becomes the eigenvalue decomposition process described by the kernel function matrix, as shown in Eq. (8).

\[
\frac{1}{n-1}Ku_i = \Lambda Ku_i.
\]  
(8)

To ensure that the original feature vector is the standard vector, namely \( u_i^T u_i = 1 \), the following processing is required, as shown in Eq. (9).

\[
u_i = \frac{1}{\sqrt{(n-1)\lambda_i}}u_i.
\]  
(9)

In combination with the definition of albino transformation matrix, \( Q \), in Eqs. (2) and (10) can be obtained.

\[
Q = \Lambda^{1/2}U^T = \Lambda^{1/2}\phi(x)V^T.
\]  
(10)

Then, the data expression after whitening processing is shown in Eq. (11).

\[
z = \Lambda^{1/2}V^T \phi(x)^T \phi(x) = \Lambda^{1/2}V^TK_x.
\]  
(11)

After whitening in Eq. (11), the data \( x \) in the original nonlinear space is mapped to the data \( z \) in the linear space; furthermore, the linear ICA algorithm is used to estimate the nonlinear independent element variable, \( s \), by optimizing the unmixing matrix \( B \) [19], as shown in Eq. (12).

\[
s = B^Tz
\]  
(12)

The above nonlinear ICA method uses kernel function in the analysis engineering, so this method is called KICA [20]. When using KICA to detect whether there is a fault in the industrial process, \( d \) nonlinear independent element \( s_d \) should be extracted from the original data, and the reconstruction error \( e \) based on \( d \) independent elements, \( s_{d} \), be calculated, and \( e \) based on the construction of appropriate monitoring measurement can effectively monitor the changes in the process, as shown in Eqs. (13) and (14).

\[
s_{d} = B_{d}^Tz,
\]  
(13)

\[
e = \Lambda^{1/2}(z - B_{d}^Tz).
\]  
(14)

### 3.2 SKICA method

Because many faults in the industrial production process are slow type faults, the process changes caused by faults are slow, reflected in the change of nonlinear independent element \( s_d \) and reconstruction error \( e \) is also slow;
therefore, even the nonlinear ICA method can only detect the fault after a long time [21].

Accumulation and cumulative sum (CUSUM) control charts are an effective means to detect micro shifts in the process, its theoretical basis is the sequential probability ratio test in the principle of sequential analysis, which determines whether the production process is in the state of statistical control by the cumulative results of previous observations [22,23]. As the process information is accumulated and the amount of information used increases, the CUSUM control chart can improve the detection sensitivity of small process deviation [24]. Based on the idea of accumulation and control chart, for the nonlinear independent element and reconstruction error in Eqs. (13) and (14), we define new cumulates and descriptors, as shown in Eqs. (15) and (16).

\[
\hat{s}_d(k) = s_d(i), \quad k < h
\]

\[
\hat{s}_d(k) = \sum_{i=k-h+1}^{k} s_d(i), \quad k = h, \ldots, N,
\]

\[
\hat{e}(k) = e(i), \quad k < h
\]

\[
\hat{e}(k) = \sum_{i=k-h+1}^{k} e(i), \quad k = h, \ldots, N.
\]

In the formula, \( h \) is the width of the sliding window.

Therefore, a new nonlinear ICA method, SKICA, is established [15]. This method first performs nonlinear processing based on ICA and then applies a sliding window to the nonlinear independent elements for cumulative sum [25]. Two monitoring statistics can be established based on SKICA model: \( I^2 \) and squared prediction error (SPE) statistics, where \( I^2 \) monitors the data changes in the independent meta-space, SPE monitors data changes in the error space, and the confidence limits of the two statistics are obtained by kernel density estimation. When SKICA is used for online monitoring, if any statistic exceeds the confidence limit (threshold), a fault occurs in the system, as shown in Eqs. (17) and (18).

\[
I^2 = \hat{s}_d\hat{s}_d^T
\]

\[
SPE = \hat{e}\hat{e}^T
\]

\section{Results and analysis}

Considering a typical industrial process continuous stirred reactor (CSTR) system as the simulation research object, to compare the effectiveness of the algorithm, first, five typical industrial process changes are simulated (as shown in Table 1), in which failures F1, F2, and F3 describe the slow change of process \( T \). Faults F4 and F5 describe the slow change of process parameters, record the process variables during the simulation, collect the data of 500 samples for each fault, and apply faults at the 201th sampling moment in each sampling process. ICA, KICA, and SKICA were used to detect faults, respectively, and their fault detection thresholds all adopted 95% confidence limits of statistics [26]. In the detection process, to facilitate the comparison of methods, if eight consecutive samples exceed the detection threshold, the time is defined as the time of fault detection.

Considering fault F1 as an example, the \( I^2 \) statistics and SPE statistics of ICA method detected the fault at the 303rd and 344th sampling time, respectively (see Figure 2), whereas the corresponding fault detection time of KICA method is 284 and 284 sampling times, respectively (see Figure 3). It can be seen that KICA method can detect fault F1 faster than the linear ICA method. SKICA method is a further improvement than KICA method for calculating the cumulative and statistics of nonlinear independent elements, the SKICA method’s cad, corpse, and SPE statistics detect the fault at 248 and 227 times, respectively (see Figure 4), which are closer to the true time when the fault occurred. Similarly, fault 2 describes the gradual change in feed temperature. Fault 3 shows the increase in the inlet temperature of cooling water. Fault 4 depicts the catalyst activity decreases. Fault 5 is the heat transfer issue in the system.

The comparison of the detection time of five faults is shown in Table 2.

In general, KICA method can detect slowly varying faults faster than ICA method, except that the statistical detection ability of F3 and FS is reduced; the KICA method can improve the detection performance of other

\begin{table}[h]
\centering
\caption{Five kinds of slow type faults}
\begin{tabular}{|l|l|}
\hline
The fault & Fault description \\
\hline
F1 & The feed concentration increased gradually at the rate of \( 5 \times 10^{-4} \) (mol/L)/min \\
F2 & The feed temperature changes gradually at a rate of 0.15 K/min \\
F3 & The inlet temperature of cooling water increased gradually at a rate of 0.05 K/min \\
F4 & Catalyst failure: catalyst activity gradually decreases \\
F5 & Heat transfer fault: the heat transfer capacity gradually decreases \\
\hline
\end{tabular}
\end{table}
faults and statistics significantly. According to the analysis of the detection results of SKICA method in Table 2, it is obvious that SKICA is superior to ICA and KICA method in the detection process of all five kinds of slow faults. Either the traditional fault detection method based on kernel fast ICA or the proposed fault detection method based on kernel timing structure ICA, their focus is on how to effectively estimate independent element characteristics from nonlinear process data; however, how to make full use of the estimated independent element features to further improve the fault detection performance is not considered. First, in the off-line modeling stage, the ICA algorithm of kernel timing structure is used to estimate the independent element sample data from the process data of normal working conditions, Gaussian mixture model is introduced to estimate the probability density function of each independent element. Based on this, the probability of sample data of independent element under normal working conditions is calculated, and then the corresponding probability threshold of each independent element is determined. Then, during the online fault detection, the kernel time-sequence structure SKICA algorithm is used to estimate the independent element sample data from the current measurement data, and according to the independent element probability density function obtained during the offline modeling, the probability of the current independent element sample data is calculated, and it is compared with the probability threshold corresponding to the independent element to determine the correlation degree between the current independent element sample data and the fault, a large weight is assigned to the sample data of independent elements with a large correlation with the fault, whereas a small weight is assigned to the sample data of independent elements with a small or unrelated correlation with the fault; therefore, at different sampling times, features of

<table>
<thead>
<tr>
<th>Fault types</th>
<th>ICA</th>
<th>KICA</th>
<th>SKICA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I^2$</td>
<td>SPE</td>
<td>$I^2$</td>
</tr>
<tr>
<td>F1</td>
<td>303</td>
<td>344</td>
<td>284</td>
</tr>
<tr>
<td>F2</td>
<td>277</td>
<td>324</td>
<td>277</td>
</tr>
<tr>
<td>F3</td>
<td>374</td>
<td>408</td>
<td>411</td>
</tr>
<tr>
<td>F4</td>
<td>412</td>
<td>462</td>
<td>394</td>
</tr>
<tr>
<td>F5</td>
<td>340</td>
<td>/</td>
<td>431</td>
</tr>
</tbody>
</table>

*/" in the table indicates that the statistics cannot detect faults.
independent elements that are highly correlated with faults can be highlighted, whereas features of independent elements that are less or unrelated to faults can be suppressed to achieve the purpose of improving fault detection performance.

5 Conclusions

The SKICA method was proposed, a typical industrial process CSTR system was considered as the simulation research object, the KICA method and SKICA method were compared and studied, the results of CSTR simulation system show that compared with the basic linear process, the slow type fault detection has good monitoring performance and can detect the small deviation in the process of sensitive, warning information can be given to slow type faults in time, it can be clearly seen that in the detection process of all five kinds of slow type faults, the fault detection capability of SKICA is better than that of ICA and KICA. Although fault detection and diagnosis based on ICA theory has attracted extensive attention of many researchers and engineers in the field of industrial process monitoring; however, due to the complexity of industrial process production equipment, the diversity of operating conditions, and the variability of uncertain factors, the collected process data usually has very complex characteristics. As a result, combined with the characteristics of industrial process data, targeted algorithm research is carried out around the SKICA method in ICA theory, and a set of process fault detection and diagnosis methods based on SKICA is established, enriching, and developing ICA theory, and it is of great theoretical and application value to meet the requirements of fault detection and diagnosis under complex industrial process data.

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