A New Fault Identification Method based on Combined Reconstruction Contribution Plot and Structured Residual

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Abstract. The existing contribution plot-based reconstruction fault identification methods suffer from low identification accuracy and serious trailing effect. In this paper, a new fault identification method is proposed based on a combination of reconstruction contribution plot and structured residual method. The fault direction vector is calculated by utilizing the structured residual method. The reconstruction contribution plot utilizes the obtained fault direction vector to accurately localize the fault variable, where the fault source can be accurately localized subsequently. The experimental results show that, compared with the traditional PCA and PPCA (PCA based on probability) reconstruction contribution method, this algorithm can accurately identify the fault variables, and reduce the influence of the fault variables on the non-fault variables.

Keywords: fault identification, reconstruction contribution plot, structured residual, fault direction vector

1 Introduction

Variously fault identification algorithms have currently evolved based on the use of fuzzy logic theory, multivariate statistical analysis, artificial intelligence and other types of algorithms. Among these algorithms, algorithms based on statistical analysis and its improvement has been widely used. Miller [1] introduced the contribution plot

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method to reflect the contribution of each variable to the statistics for the first time. Based on this work, various PCA model-based contribution plot methods have been proposed subsequently, including complete decomposition contribution, partial decomposition contribution, diagonal contribution, angle-based contribution and reconstruction-based contribution (RBC). The traditional reconstruction contribution plot method would increase the contribution of non-fault variables when localizing the fault variables, it is necessary to combine multivariate statistical methods and analytical methods to investigate and decouple the fault vectors by constructing appropriate residuals, where the accuracy of fault separation can be improved [3-4]. When the fault range is set to a larger value [5], RBC can identify the single-variable fault with 100% accuracy. However, the accuracy of multivariable fault identification [6] cannot be 100%.Therefore, it is urgent to study new methods to improve the traditional reconstruction contribution method.

A weighted RBC-based [7] fault identification method was proposed, which can reduce the impact of fault variables on non-fault variables. By leveraging the missing values, an improved reconstruction contribution plot method was proposed to significantly reduce the "pollution effect" on non-fault variables [8]. A kernel principal component analysis (KPCA) based fault identification method is proposed based on data reconstruction [9], it can desirably avoid the single-variable fault in the traditional KPCA algorithm and obtain reduced computational complexity of the data indices. To overcome the inconsistent monitoring results with two different monitoring statistics, a probabilistic principal component analysis-based reconstruction contribution plots (PPCA-RCP) was proposed by using monitoring statistics of a unified metric [10]. The problem of inaccurate fault variables localization by traditional contribution plot analysis method is further investigated, where a new fault localization method was proposed by combining the nearest neighborhood imputation and the traditional contribution plot [11-12].

The fault variable acquisition process is relatively complicated in complex systems, where the identification accuracy and real-time performance are difficult to be guaranteed. Therefore, a reconstruction contribution plots combined structured residual (RCP-SR) method is proposed based on reconstruction contribution plot and structured residual. The structured residual method is used to calculate the fault variable direction and the fault variable. Subsequently, the direction data is fed to the reconstruction contribution map for accurate fault localization, which can effectively avoid the trailing effect and improve the fault identification rate.

2 Reconstruction contribution Method

The contribution plot can be utilized to visualize the results of fault variables with a bar chart, which can reflect the severity of the fault variables and visualize the impact of the fault variable on the non-fault variable. The contribution rate of all principal variables is reflected in the contribution plot, which can be used to intuitively observe the statistical contribution and determine an abnormal data.

Duo to single fault variable, the fault sample x can be decomposed as normal and faulty components,

$$x = x^* + \xi_i f_i \tag{1}$$

where x^* is the normal component, ξ_i is the direction vector of the fault and f_i is the fault amplitude of the fault variable.

The reconstructed value z_i can be expressed as follow,

$$z_i = x - \xi_i f_i \tag{2}$$

The statistics D of observed samples can be expressed as,

$$D(x) = xC^{-1}x^T \tag{3}$$

For each variable $x_i (i = 1, 2, \cdots, m)$, the statistical contribution of monitoring statistics D from x_i to x can be expressed as,

$$c_i^D = (xC^{-0.5}\xi_i)^2 \tag{4}$$

where ξ_i is the direction vector of the i-th fault variable vector.

According to (4.3), the monitoring measure of the reconstructed sample z_i can be expressed as follows,

$$D(z_i) = z_i C^{-1} z_i^T \tag{5}$$

If the method is to minimize the monitoring measure of reconstruction sample $D(z_i)$, it can be obtained by taking the partial derivative of f_i as follow

$$\frac{d(D(z_i))}{df_i} = 0 \tag{6}$$

The amplitude f_i can then be expressed as,

$$f_i = (\xi_i^T C^{-1} \xi_i)^{-1} \xi_i^T C^{-1} x^T \tag{7}$$

When the fault occurs, the reconstruction method is utilized to localize the fault. When the fault direction ξ_i is correctly localized, the fault variable identification is correct if the monitoring measure of reconstruction sample $D(z_i)$ is lower than the control threshold. Otherwise, the fault variable identification is incorrect.

For a single variable, the reconstruction contribution[2] can be calculated as,

$$c_i^{RBC} = index(x) - index(z_i) = xC^{-1}\xi_i (\xi_i^T C^{-1} \xi_i)^{-1} \xi_i^T C^{-1} x^T \tag{8}$$

For multiple variables, the reconstruction contribution[13] can be calculated as,

$$c^{RBC} = xC^{-1}\Xi(\Xi^T C^{-1}\Xi)^{-1}\Xi^T C^{-1} x^T \tag{9}$$

where Ξ is the matrix constructed by the fault direction vector.

3 Structured Residual

3.1 The Principle of Structured Residual

From the analysis in the previous section, it can be seen that the fault direction vector ξ_i directly determines the fault localization accuracy. In order to improve the accuracy, it is required to obtain the correct fault direction vector ξ_i. In this paper, the fault direction vector ξ_i based on PCA structured residual is proposed, which is further illustrated as follows.

Since the original residual $t_e = P_e^T x$ represents the deviation of the monitored variable from the principal component subspace (PCS) at each sampling time, the original residual can be used to construct the structured residual. Since the relationship between PCS and residual Subspace (RS) is orthogonally complementary in space, it can be obtained for system with fault,

$$P_e^T x_0^* = 0 \tag{10}$$

$$t_e = P_e^T x = P_e^T \xi f = \phi f \tag{11}$$

where x_0^* represents the true variable value without impact of measurement and noise, P_e^T represents the fault mapping vector and f represents the incident matrix.

Based on (10) and (11), it can be obtained,

$$\phi = P_e^T \xi \tag{12}$$

In particular, ϕ represents the mapping matrix from individual fault to original residual t_e, where each column represents the fault mapping coefficient vector from one corresponding fault to original residual t_e.

By introducing the transformation matrix G, the structured residual γ is constructed by the original residual,

$$\gamma = Gt_e = G\phi f = Hf \tag{13}$$

where the number of structured residuals is the number of rows in G and $H = G\phi$ represents the mapping matrix from each fault to the structured residual. The i-th row in the incidence matrix is represented by γ_i. When corresponding elements in the i-th row is 0, it indicates that the residual has no response to the fault, i.e., the i-th row g_i^T of G is orthogonal to the corresponding columns in ϕ.

$$g_i^T \phi |_{fcode=0}^i = 0 \tag{14}$$

where $\phi |_{fcode=0}^i = 0$ represents a matrix consisting of the columns corresponding to the row 0 element of the incidence matrix. Since the number of rows in ϕ is m, the solution exists for (14) and there exists the following relationship between its rank and the number of rows in ϕ,

$$rank[\phi |_{fcode=0}^i = 0] < m \tag{15}$$

To guarantee that γ_i corresponds to the fault from the 1 value in i-th row of the incidence matrix, the i-th row of the incidence matrix should satisfy the following necessary condition,

$$rank[\phi |_{fcode=0}^i = 0 \quad \varphi_j^1] = rank[\phi |_{fcode=0}^i = 0] + 1 \tag{16}$$

where φ_j^1 is the column in ϕ not belonging to the column of $\phi |_{fcode=0}^i = 0$.

The mapping vector matrix and the incidence matrix directly determine the transformation matrix, and it can directly obtain P_e^T with PCA statistical model.

4 The fault identification algorithm flow based on reconstruction contribution plot and structured residual

Based on the reconstruction contribution plot and structured residual method as described in the previous two sections, a fault identification algorithm is designed by combining the reconstruction contribution plot and structured residual, where the algorithm flow is summarized in Fig. 1. The basic idea is briefly described as follows. Firstly, the fault direction vector ξ_i is calculated by utilizing the structured residual algorithm. Secondly, the obtained fault direction vector is fed into the reconstructed contribution plot for accurate fault variable localization. The steps of the algorithm are further summarized as follows.

(1) The fault direction vector ξ_i can be obtained with the structured residual algorithm;

(2) The fault sample can be expressed as normal and faulty components, i.e., $x = x^* + \xi_i f_i$;

(3) The PCA based method is utilized to reconstruct the fault variable by utilizing $z_i = x - \xi_i f_i$;

(4) According to the statistics of observed sample $D(x) = xC^{-1}x^T$, the reconstruction monitoring measure can be expressed as $D(z_i) = z_i C^{-1} z_i^T$;

(5) By taking partial derivative of reconstruction monitoring measure, i.e., $\frac{d(D(z_i))}{df_i} = 0$, the fault amplitude can be obtained as $f_i = (\xi_i^T C^{-1} \xi_i)^{-1} \xi_i^T C^{-1} x^T$;

(6) The contribution from the fault types of a single fault variable and multiple fault variables can be calculated with $c_i^{RBC} = xC^{-1}\xi_i (\xi_i^T C^{-1} \xi_i)^{-1} \xi_i^T C^{-1} x^T$ and $c^{RBC} = xC^{-1}\Xi(\Xi^T C^{-1}\Xi)^{-1}\Xi^T C^{-1} x^T$, respectively;

(7) The fault source can be accurately localized according to the identified fault variables.

5 Simulation validation and analysis

5.1 Simulation Environment Setting

The TE process is a realistic simulation of the actual production plant. The entire process consists of five operating units, i.e., reactor, product condenser, gas-liquid separator, recycle compressor and stripper. Four types of gaseous materials mainly participate in the reaction, which generates two types of products G and H via chemical reaction. Moreover, a small amount of inert gas B and gaseous by-products are removed by venting during the product feed, where 22 measurement variables are used in the continuous process. There are 21 types of faults in the TE process, which is shown in

Table 1. In this section, fault 1 and fault 14 are used as examples to validate the practicability of the algorithm, wherein the variables associated with fault 1 are x_1, x_4 and x_{18}, and the fault variables associated with fault 14 are x_9 and x_{21}.

Table 1 A summary of the fault types in the TE process

Number	Process Variables	Types
Fault 1	Feed ratio of Material A/C changes	Step
Fault 2	Composition ratio changes	Step
Fault 3	Temperature change of Material D	Step
Fault 4	Temperature change of the reactant cooling water inlet	Step
Fault 5	Temperature change of the reactant cooling water inlet	Step
Fault 6	Loss of Material A	Step
Fault 7	Head loss of Material C	Step
Fault 8	Composition changes of Materials A, B, C	Random
Fault 9	Temperature change of Material D	Random
Fault 10	Temperature change of Material C	Random
Fault 11	Temperature change of reactor cooling water inlet	Random
Fault 12	Temperature change of condenser cooling water inlet	Random
Fault 13	Reaction kinetic constant change	Slow shifting
Fault 14	Reactor cooling water valve	Sticky
Fault 15	Condenser cooling water valve	Sticky
Fault 16-21	Unknown	Unknown

Table 2 Fault Description

Fault Number	Fault Description	Fault Variables	Fault Type
Fault 1	Feed ratio of Material A/C	x_1, x_4, x_{18}	Step
Fault 14	Reactor cooling water valve	x_9, x_{21}	Sticky

5.2 The analysis and comparison for simulation

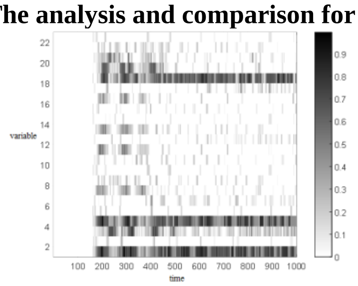


Fig. 1-a basic RBC method

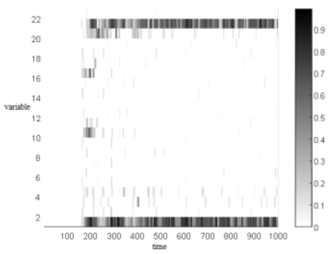
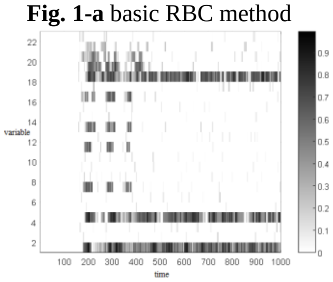


Fig. 1-b PCA-MRCP method



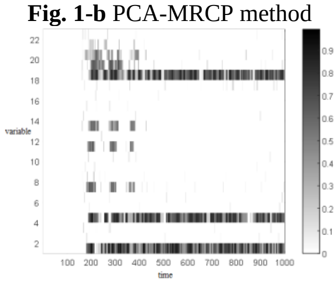


Fig. 1-c PPCA-RCP method **Fig. 1**-d RCP-SR method

By comparing RBC, PCA-MRCP, PPCA-RCP and proposed RCP-SR methods, the location analysis of fault 1 is shown in Fig. 1-a, 1-b, 1-c, and 1-d. In these figures, the darkness of the shadow color represents the contribution rate of reconstruction, among which the darker color represents the larger contribution rate, and the variable with a larger contribution rate is defined as the fault variable. From these figures, it can be seen that there is a trailing effect from the time 160 to 400, because the reason is that the variables are not independent of each other in the initial stage of the fault. Although there are certain relationships between the variables after time 400, the system will reach a new stable state due to the self-regulation of the control system. The reconstruction contribution plot based on traditional RBC method is relatively chaotic, resulting in some non-faulty variables being misidentified as fault variables. Ultimately, it affects the identification and leads to trailing effects. The PCA-MRCP method suffers from the inconsistent fault variables identification issue when different PCA metrics are used, where the trailing effect is also generated. The PPCA-RCP method is better than the traditional method. Consistent with the previous process analysis, x1 x4 and x18 can be correctly identified to be the most obvious three fault variables. The RCP-SR method can overcome the inconsistency of the localization results when monitoring the statistics of different metrics based on the PCA-MRCP method, and can localize the fault variables more accurately and effectively.

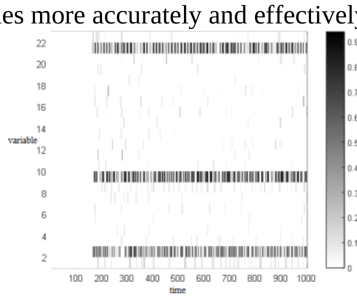


Fig. 2-a basic RBC method

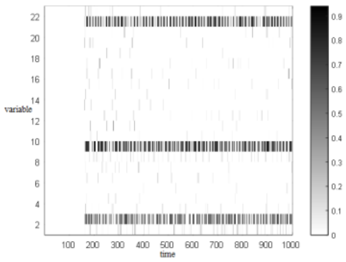


Fig. 2-b PCA-MRCP method

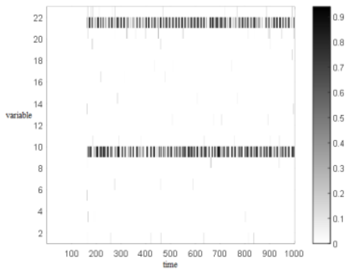


Fig. 2-c PPCA-RCP method

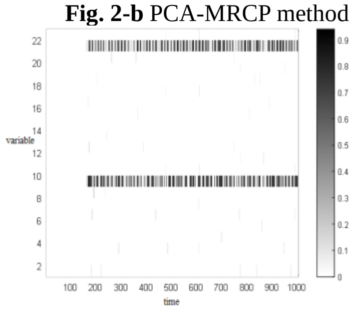


Fig. 2-d RCP-SR method

The fault localization analysis is shown in Fig. 2-a, 2-b, 2-c and 2-d. Although the traditional RBC method can correctly identify the fault variable to be x2, x9 and x21, the localized fault variables are not consistent with the actual fault variables, where the trailing effects are rather significant. Although the PCA-MRCP method can localize the fault variables, the localization results are inconsistent and affect determination of the fault variables. The PPCA-RCP method can localize the fault variables accurately, but the trailing problem exists. The proposed RCP-SR can desirably resolve the drawbacks of the above methods with significant superiority.

6 Conclusion

A new fault vector direction vector calculation algorithm is developed based on structured residuals, and a fault identification algorithm is proposed based on reconstruction contribution plot and structured disability. Simulation example of the algorithm is also designed based on the fault identification algorithm workflow. The simulation results show that the proposed algorithm can achieve superior performance compared to the conventional RBC, PCA-MRCP and PPCA-RCP methods, which can obtain reduced impact on non-fault variables, suppression of trailing effects and improved fault localization accuracy.

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