A Fault Detection and Isolation Scheme for Dual-channel Speed Sensors

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***Abstract*—High-speed train dual-channel speed sensors are often influenced by factors like dusts, vibration, temperature changes, which easily cause false or miss alarm, even wrong isolation. The experimental comparison method commonly used in practical engineering, this method cannot detect faults in time or accurately isolate multiple faults. In this paper, a novel fault detection and isolation (FDI) scheme for dual-channel speed sensors is proposed by using the improved principal component analysis (PCA) and the improved reconstruction-based contribution plots (IRBCP). Take the dual-channel speed sensor of high-speed train as an example, experimental results show that the proposed scheme can satisfy FDI requirements of speed sensors, and is accurate and effective.**

Keywords—Dual channel speed sensor; Fault detection and isolation (FDI); Improved PCA; Improved Reconstruction-based Contribution Plots (IRBCP).

I. INTRODUCTION

It is vital to implement FDI of speed sensors for ensuring the safe and effectiveness of high-speed train. Dual-channel speed sensor is an important part of the high-speed train control system, and because its two-channel mutual verification function, it is more widely applied to the high-speed train. At present, the experimental comparison method [1] is a common method for FDI of speed sensors: fault is isolated by comparing the speed of each axis with the reference axis speed. Although this method is commonly used in practice, in terms of its working principle and application, there are still the following shortcomings: noise interference leads to false or not timely detection, no further check until the train frequently idling and taxiing, lack of quantitative standard for the reference axis speed, setting thresholds only by experience, unable to isolate faulty multiple axes and channels at the same time, et al.

There are many FDI methods for speed sensors, of which the multivariate statistical analysis method is to use the correlation between multiple variables of the process to diagnose the process. This method does not need to have a deep understanding of the structure and principle of the system, and the algorithm is simple and easy to implement. Principal Component Analysis (PCA) is frequently used in the monitoring of multivariate statistical processes, which is also applied in rolling bearing, power circuit fault diagnosis and data dimensionality reduction. When applying PCA model in fault detection, different statistics may get different results. Apart from this, there is the tailing effect [2] when using contribution plots method to isolate faults. Reference [3] reconstructs the data along the direction of faults, calculates the reconstruction-based contribution (RBC) of each variable and achieves fault diagnosis in this way. A rigorous mathematical proof of the RBC method is reported in [4], which guarantees the RBC method has a higher fault isolation accuracy than the contribution plots method.

With the redundant information collected by sensors, PCA can be further improved to realize fault diagnosis. For example, Xu et al. [5] conduct a PCA-based fault sensor reconstruction theory study and analyzed the data in the residual subspace changes to reconstruct faulty sensors. Reference [6] considers the introduction of weighting factors to distinguish the contribution values of cross terms in different directions, which effectively improves the correct rate of online fault diagnosis of sensors. A recursive principal component analysis method [7] is reported to establish an updated model with the latest data sets, and to adaptively monitor faults to prevent false alarms.

In this paper, the demand for high-speed train dual-channel speed sensors' FDI is taken as the traction, and the PCA-based technology is used as a tool. For the defects mentioned above, an accurate and effective solution is proposed: using the "detectable fault amplitude" [8] to select the appropriate statistics and further refinement, fault isolation is achieved by using IRBCP method [9,10]. The effectiveness of the proposed scheme was tested on the experimental platform and LabVIEW simulation platform, and compared with the traditional PCA and Kalman filter. The experimental results show that this scheme can detect and isolate single or multiple faults of the speed sensor on the high-speed train more accurately.

The rest of this paper is arranged as follows, as shown in Fig1: Section 2 gives a brief introduction to the improved PCA, the IRBCP, and a detailed description of the proposed scheme. Section 3 shows a verification case using actual collected data. Finally, conclusions and future work come in section 4.

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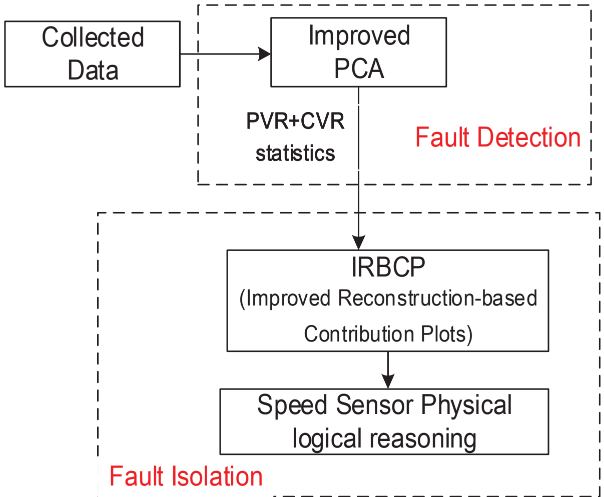

Figure 1. Framework of the paper

II. METHODOLOGY

In this section, the relevant knowledge for the methods mentioned in this paper are introduced.

A. Improved PCA (Principal Component Analysis)

Step 1: Establish the PCA model

Normalize the historical data set $X \in \boldsymbol{R}^{(m\times n)}$, and after the principal element decomposition:

$$X = \tilde{X} + E = \boldsymbol{P}\boldsymbol{P}^T x + \tilde{\boldsymbol{P}}\tilde{\boldsymbol{P}}^T x \quad (1)$$

where $\tilde{X}$ represents the principal element space, E represents residual space after PCA modeling, $\boldsymbol{P} \in \boldsymbol{R}^{m\times k}$ is the load matrix, which consists of the k former vector in the feature vector of the sample covariance matrix and $\tilde{\boldsymbol{P}} \in \boldsymbol{R}^{m\times(n-k)}$ consists of the (n-k) following vector of the covariance matrix feature vector.

After constructing the PCA model, the abnormal signal is detected by calculating Hawkins T^2 statistics and Q statistics of the test sample and comparing it with the threshold $\delta_T^2, \delta_{SPE}^2$ obtained by the normal training sample.

Hawkins T^2statistics:

$$T^2 = \left\| \boldsymbol{\Lambda}_{k+1,m}^{-1/2} \tilde{\boldsymbol{P}}^T x \right\|^2 \leq \delta_T^2 \qquad (2)$$

Qstatistics:

$$Q = \|(\boldsymbol{I} - \boldsymbol{P}\boldsymbol{P}^T) \cdot x\|^2 \leq \delta_{SPE}^2 \qquad (3)$$

$\boldsymbol{\Lambda} = diag\{\lambda_1, \lambda_2, \ldots, \lambda_k\}$represents a matrix composed of the eigenvalues of the sample covariance matrix, λ_i represents the eigenvalue of the correlation coefficient matrix R.

Step 2: Select fault detection statistics

Defining the detectable fault amplitude is the size of the corresponding control limit of each statistic. From the geometrical point of view, the Qstatistics control limit $\delta_{SPE}^2$is same to any principal element, but Hawkins T^2 statistics control limits $\delta_T^2$is disparate for different principal elements [6]. Therefore, the detectable fault amplitude is used as a sufficient condition for judging anomaly, and the corresponding control limit of each principal direction based on PCA model are calculated and compared, then an appropriate detection statistic is selected.

Usually when system deviations are ignored, the sensor test value can be expressed as [11]:

$$X_k = X^* + f_k \zeta_j \qquad (4)$$

where X_k is the fault data, X^* is normal data, f_k is the magnitude of the fault, and ζ_j is the fault direction vector. According to the norm triangle inequality after calculation, the sufficient condition for the Q statistics to detect faults:

$$|f_k|_{SPE} \geq \frac{2\delta_{SPE}}{\|\tilde{\boldsymbol{P}}\tilde{\boldsymbol{P}}^T \zeta_j\|^2} \qquad (5)$$

Similarly, the sufficient condition for the Hawkins T^2statistic to detect faults:

$$|f_k|_{T^2} \geq \frac{2\delta_{T^2}}{\left\| \boldsymbol{\Lambda}_{k+1,m}^{-1/2} \boldsymbol{P}^T \zeta_j \right\|^2} \qquad (6)$$

Step 3: Refine fault detection statistics

In practical applications, there are some problems in relying solely on a certain statistic to judge faults: it can only detect whether the process has changed, but cannot reveal the cause of the change. Therefore, this paper refines the statistics for further fault detection: decomposes the Q statistics into the principal-component-related variable residual (PVR) and the common variable residual (CVR) [12].

$$PVR = x_s(\boldsymbol{I} - \boldsymbol{P}_s \boldsymbol{P}_s{}^T) x_s^T \quad (7)$$

$$CVR = x_{n-s}(\boldsymbol{I} - \boldsymbol{P}_{n-s} \boldsymbol{P}_{n-s}{}^T) x_{n-s}^T \qquad (8)$$

where $x_s$is the process variable associated with the principal element. The subscripts *s* and *n-s* corresponding to the principal-component-related variable in the data matrix X and the common variable in the load matrix P. $\rho(x_i, y)$ is the complex correlation coefficient between the i-th process variable and the k-th principal element. The square of complex correlation-coefficient γ_i can be directly calculated:

$$\gamma_i = \rho^2(x_i, y) = \sum_{j=1}^{k} \lambda_j p_{i,j}^2 \qquad (9)$$

Therefore, the Q statistics value is just divided into two parts:

$$Q_\alpha = PVR_\alpha + CVR_\alpha = w_{PVR} Q_\alpha + w_{CVR} Q_\alpha \quad (10)$$

$$w_{PVR} = 1 - \sum_{i\in PV} \gamma_i / \sum_{i=1}^{n} \gamma_i \qquad (11)$$

It can be seen from equations (10) and (11) that When Q statistics is subdivided into PVR and CVR, not only the fault detection is more accurate, but also some fault isolation information is provided: if the PVR exceeds the control limit, the faulty variables belong to the Principal-component-related Variable (PV)set, and the fault variable belongs to the Common Variable (CV) set. The specific improved PCA for detecting anomaly is shown in Fig.2.

B. Improved Reconstruction- Based Contribution Plots (IRBCP)

Reference [4] proposes the reconstruction-based contribution plots method for fault isolation, however it is only work well for the single faulty variable. When multiple variables are faulty at the same time, because of the serious tailing effect and the lack of quantitative terms for fault isolation, it is impossible to solve the problem of multi-fault isolation of high-speed train dual-channel speed sensor.

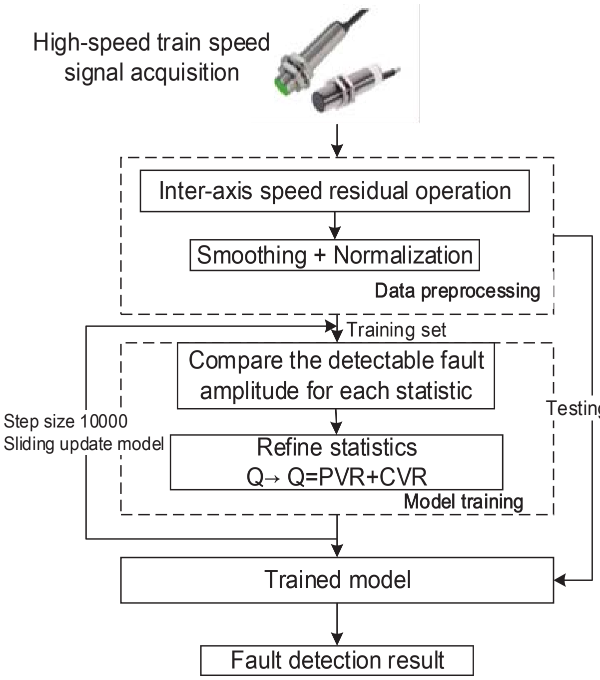

Figure 2. Improved PCA fault detection process

The preprocessed data is moved along the corresponding fault subspace direction toward the principal element space based on equation (4), and the reconstruction result $\boldsymbol{z}_i$ is as follows:

$$z_i = x - \zeta_i f_i \qquad (12)$$

When the fault direction of the isolation is accurate, take the comprehensive index φ [13] as an example, the monitoring index $Index(z_i)$:

$$\varphi(x) = \frac{T^2}{TUCL} + \frac{Q}{QUCL} = x^T \phi x \qquad (13)$$

$$S = (x - \Xi_i f_i)^T \Phi (x - \Xi_i f_i) \qquad (14)$$

TUCL and QUCL are the 99% confidence control limits of Q statistics and Hawkins T^2statistics, respectively. $\boldsymbol{\Xi}_i$ is the fault direction matrix. The task of fault reconstruction is to find f_i and obtain the minimum value$Index(z_i)$, so we can get the equation (14):

$$f_i = (\Xi^T{}_i \Phi \Xi_i)^+ \Xi^T{}_i \Phi x \qquad (15)$$

$(\cdot)^+$ is the matrix pseudo-inverse operation. Variable x_i reconstruction-based contribution(RBC) due to the comprehensive index φ is defined as [4]:

$$RBC_i^{Index} = \|\xi_i f_i\|_M^2 \qquad (16)$$

$$RBC_i^{Index} = x^T \Phi \Xi_i (\Xi_i^T \Phi \Xi_i) \Xi^{+T}_i \Phi x \qquad (17)$$

In order to solve the problem of multi-fault isolation of high-speed train speed sensor, this paper introduces the IRBCP method [9,10]. Firstly, define the fault set X_f as an empty set, and calculate the RBC value of the combination of X_f and each non-fault variable in turn. Add the maximum RBC value corresponding variable to the fault variable set and continue to iteratively calculate the RBC value of the fault variable set $X_f$and reconstruct the monitoring indicator $Index(z_i)$, until 95% sample satisfies the two conditional equations (equations (18) and (19)), and then isolates the fault according to the explicit physical correspondence between the fault variable and the speed sensor channel.

$$\Delta_r \triangleq \varphi(x) - \zeta^2 \qquad (18)$$

ζ^2 [10] is the control limit of the comprehensive index φ, Δ_r is the control limit corresponding to the RBC.

When the fault variable set $\boldsymbol{X_f}$ direction is accurate, Condition 1: $RBC_{X_f} \geq \Delta_r$.

Condition 2: If the fault variable set $X_f$direction is correct, then [14] is satisfied:

$$Index(z_i) = (x - \Xi_i f_i)^T \Phi (x - \Xi_i f_i) \leq \zeta^2 \qquad (19)$$

C. Proposed FDI Scheme

The high-speed train dual-channel speed sensor FDI framework proposed in this paper is shown in Fig.3 in detail. It is characterized by the ability to handle multi-fault signal detection and isolation under different working conditions, which has important practical application value.

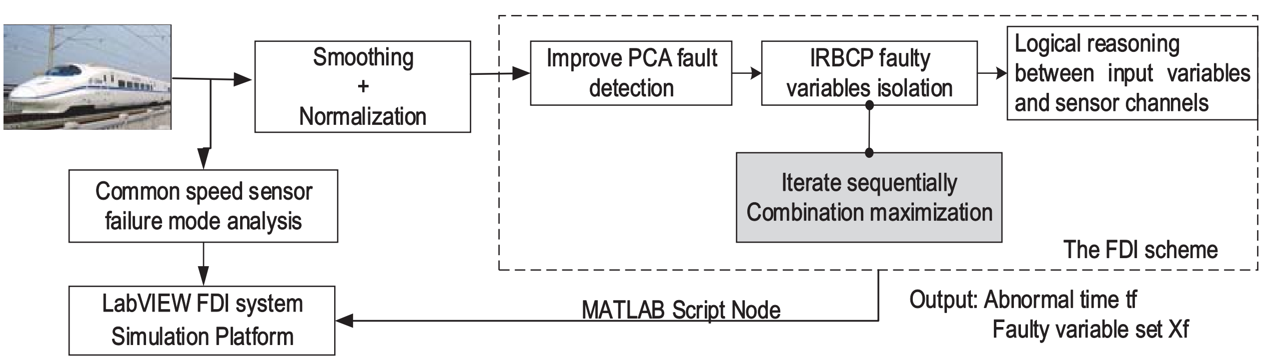

Figure 3. FDI system structure of speed sensors

III. CASE VALIDATION

A. Data collected

As shown in Fig.4, through this test platform, high-speed train dual-channel speed sensor data can be collected, and relevant physical parameters are shown in TABLE I.

In order to verify the actual feasibility of this scheme, the five most common fault types of high-speed train speed sensor are summarized according to engineering experience: Blocking fault, disconnection fault, constant bias fault, drift fault and precision-reduction fault. According to signal characteristics, inject different types, degrees and channels faults to obtain training data and testing data by LabVIEW.

TABLE I.TEST PLATFORM PARAMETERS

Tset platform	
Parameter	***Value***
Motor Speed	900-1500 r/min
Wheel-diameter	860mm
Circuit-resistance	390Ω
Frequency	0~20kHz

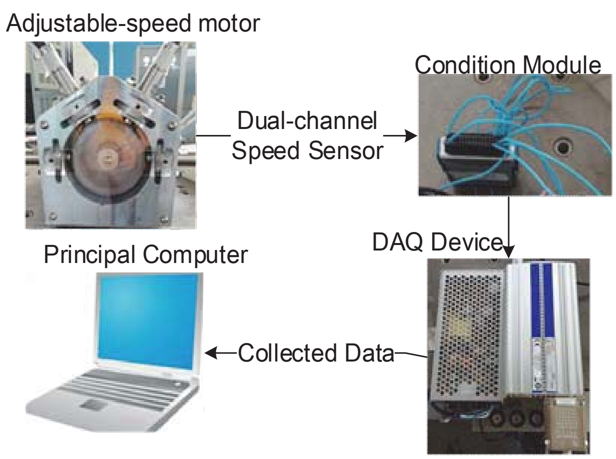

Figure 4. Test Platform

B. Fault detection and isolation (FDI)

The amount of data processed at one time is $X \in \boldsymbol{R}^{(10000\times6)}$, the fixed windows move sequentially along the time axis, constantly updating the PCA model. Apply the improved PCA method to determine the signal anomaly moment, and then use IRBCP method to get the complete faulty variable set. Finally, the positioning of multiple faults are realized according to the correspondence between the input variables and the physical structure of the sensor channels. On the LabVIEW front panel, the indicator light indicates the faulty channel location, and the PVR and CVR curves also provide some fault causes.

Take the 2nd channel precision-reduction fault as an example, and calculate Q statistics of the input variable is less than Hawkins T^2 statistics, therefore refine Q statistics to get PVR and CVR curves. As shown in Fig.5, the traditional PCA method detects the abnormal point is 3422. But the improved PCA results are: the PVR curve is normal, the CVR statistics discover the abnormal point is 4002, which is closer to the actual fault injection point 4000. When the point greater than the threshold is detected, it is compared with the point of the actual fault injection; if the error is outside 0.1%, the fault detection is considered to be failed. Also, it indicates that faulty variables are included in the CV set, which correspond to the conclusion that the complete faulty variable set is (X_1, X_4, X_5) as shown in Fig.6.

For fault detection, Tab.2 gives a comparison of the traditional PCA method, Kalman filtering method and the scheme proposed in this paper.

$$\text{correct rate} = \frac{N_{i,correct}}{N_i} (i = 1,2, \ldots ,6)$$

$N_{i,correct}$: the number of cases in which *i-th* failure type is correctly isolated.

N_i: the total number of *i-th* failure type cases.

It can be seen from the Table II that the detection accuracy of this scheme for the precision-reduction fault is much higher than the other two methods, but the detection effects of the three methods of blocking and disconnection are not much different.

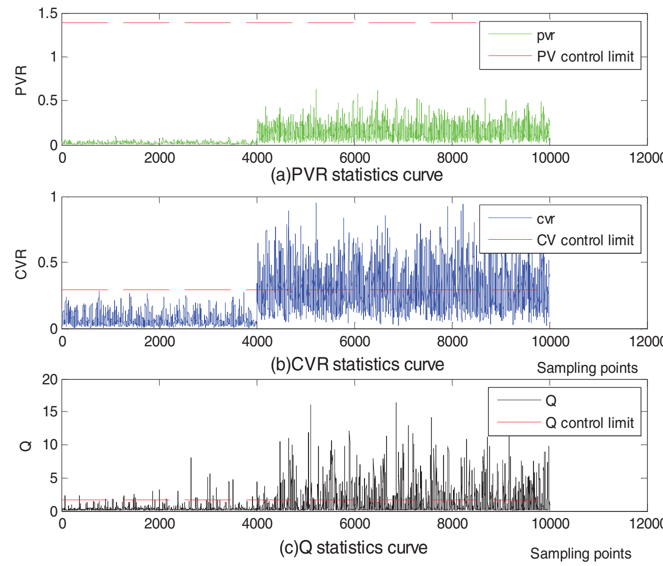

Figure 5. 2nd channel precision-reduction fault detection

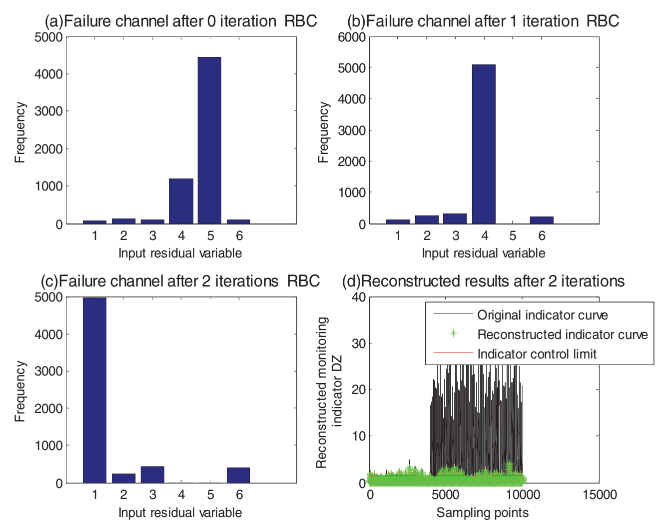

Figure 6. 2nd channel precision-reduction fault detection and reconstruction results

TABLE II. FAULT DETECTION ACCURACY COMPARISON RESULTS

Fault Types (cases)	*Q statistics*		*Kalman filter*		*Improved PCA*	
	False Negatives	Correct rate	False Negatives	Correct rate	False Negatives	Correct rate
Stocking（14）	3	78.57%	0	100.00%	0	100.00%
Drift（28）	2	92.86%	8	71.43%	0	100.00%
precision-reduction (28)	7	75.00%	20	28.57%	0	100.00%
Constant bias（28）	0	100.00%	19	32.14%	0	100.00%
Virtual Connection（44）	10	77.27%	0	100.00%	3	93.18%
Disconnection（29）	6	79.31%	3	89.66%	4	86.21%
Total (171 cases)	28	83.63%	50	70.76%	10	94.15%

IV. CONCLUSIONS AND FUTURE WORK

This paper proposes the FDI scheme for high-speed train dual-channel speed sensors. The architecture of this scheme includes signal acquisition preprocessing, improved PCA fault detection and IRBCP method fault isolation. PCA model is established through the collected historical data, and the appropriate fault detection statistics are selected and refined by the monitoring data to realize fault detection and provide some fault cause information. Then, obtain complete faulty variables by IRBCP method, and isolate single or multiple faults based on the physical correspondence between the input variables and sensor channels. Therefore, this FDI scheme can satisfy the requirement of high-speed train speed sensors, and has important engineering application value. Although the scheme proposed has achieved some results in the above work, there are also sensor FDI limited to several common fault types, which fail to effectively implement complex fault FDI and fault classification. Future work will focus on in-depth research on complex fault diagnosis and even prediction.

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