Dynamic Fault Detection Method of Traction Systems in High-Speed Trains Based on Joint Observer

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Abstract. This paper proposes a joint state observer based on deep learning for traction systems in high-speed trains. For actual systems, the signal collected by multiple sensors contains different variables, and each variable will reflect the state of the systems. However, most researchers construct the state estimation strategy without consideration of relations between variables, reducing the accuracy of fault detection. Therefore, how to analyze the correlation of different variables and design the data-driven observer becomes the difficult problem. This paper designs a data-driven joint output observer for traction system of high-speed trains. The joint distribution function is constructed by the marginal distribution of different variables and the resultant weight of the joint model is calculated by Kendall rank correlation coefficient. In the end, the proposed method is verified on a pilot-scale experimental platform and traction systems in high-speed trains.

Keywords: Fault detection · High-speed trains · Joint observer

1 Introduction

In recent years, the high-speed trains have gradually become one of the convenient ways for people to travel [1]. Traction control systems is of great significance to ensure the efficient operation of high-speed trains. Once any fault occurs, it may cause great loss of personnel and property [2]. Therefore, effective fault detection of tractions systems is a hotspot in recent years.

Recently, because of the better applicability and high accuracy, much attention has been paid to data-driven fault detection methods [3]. At present, data-driven fault detection methods for industrial systems can be divided into three categories: multivariate statistical analysis-based methods, deep learning-based methods, and subspace identification-based methods. Commonly adopted multivariate statistical analysis-based fault detection methods such as principal component analysis (PCA) [4], slow feature analysis (SFA) [5], and canonical variate analysis (CVA) [6], depend on different variables to design detection methods directly. In [7], an improved dynamic kernel PCA

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is proposed based on local preserving projections for dynamic nonlinear systems. In addition, A weighted probabilistic SFA and improved CVA are constructed for process monitoring of dynamic systems in [8] and [9]. Although this type of method has been successfully extended to dynamic systems, it is difficult to obtain robust detection results due to the complexity of noise and disturbance. Benefiting from the rapid development of neural networks, deep learning-based methods occupy the mainstream of current research. Its low complexity of model designing brings great convenience for researchers and engineers. For example, Zhang et al. [10] proposed a full feedback dynamic neural network with exogenous input. The noise of collected data is reduced to obtain accurate results. Besides optimizing the network model, improving the training method can also enhance the dynamic performance of the algorithm [11]. However, it is also difficult to deal with the disturbance and noise. In the multi-sensor monitoring environment, enhancing the interpretability of deep learning methods is still a big problem to deal with. The subspace identification-based strategy not only realizes the analysis of dynamic characteristics, but detects faults through residual generator by data-driven observer. Motivated by this, this paper proposed a joint data-driven observer for the fault detection task of traction systems. The main contributions and innovations of this study include:

(1) A joint observer based on the copula function is constructed for traction systems.
(2) The fault detection strategy based on data-driven designs is introduced.
(3) Different experiments including motor platform and traction systems are used for verification.

The paper is organized as follows. In Sect. 2, the proposed data-driven fault detection scheme is introduced. Section 3 shows the experiment results by different aspects. In Sect. 4, the discussions about the open problems and perspectives are given. Section 5 is the conclusions and future works of this study.

2 The Proposed Data-Driven Fault Detection Scheme

The purpose of this paper is to design a joint data-driven fault detection method for traction systems in high-speed train. The framework of the proposed method is shown in Fig. 1.

2.1 Systems Description

Consider the LTI model of systems as

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + \omega(k) \\ y(k) &= Cx(k) + Du(k) + \upsilon(k) \end{aligned} \tag{1}$$

where $x \in \mathcal{R}^{k_x}$ represents the state of systems; $u \in \mathcal{R}^{k_u}$ and $y \in \mathcal{R}^{k_y}$ are input and output of systems, respectively; A, B, C, and D stand for the system matrices with known dimensions; $\omega \in \mathcal{R}^{k_x}$ and $y \in \mathcal{R}^{k_y}$ are white noises with the assumption that $\omega \sim \left(0, \sum_{\omega}\right)$ and $\upsilon \sim \left(0, \sum_{\upsilon}\right)$.

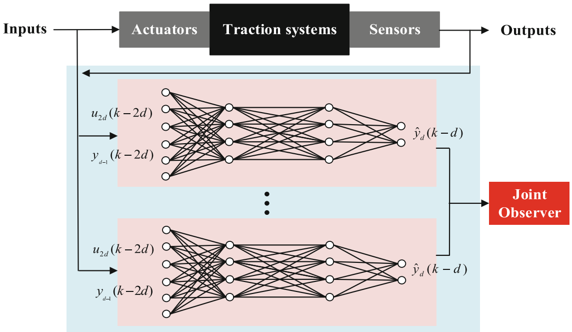


Fig. 1. The framework of proposed joint observer model

The full-order observer introduced in [12] is given below.

$$\begin{aligned} \hat{x}(k+1) &= A\hat{x}(k) + Bu(k) + L(r(k)) \\ \hat{y}(k) &= C\hat{x}(k) + Du(k) \end{aligned} \tag{2}$$

where $r(k)$ stands for the residual of system output.

In data-driven scheme, the residual generator can be obtained by using the kernel representation $\mathcal{K}$ and left coprime factorization introduced in [13]. These definitions are given as

$$\mathcal{K}\begin{bmatrix} u(z) \\ y(z) \end{bmatrix} = 0, \mathcal{K} := \begin{bmatrix} -\hat{N}(z) & \hat{M}(z) \end{bmatrix} \tag{3}$$

According to the definitions above, the residual generator (4) can be used to fault detection.

$$r(z) = \hat{M}(z)y(z) - \hat{N}(z)u(z) \tag{4}$$

2.2 Data-Driven Joint Observer Based on Correlation Measure

To design a joint model, the important lemma [14] is given as follows.

Lemma 1 (Sklars theorem): For a random vector X with cumulative distribution function F and univariate marginal cumulative distribution functions $F_1, \cdots, F_d$. *There exists a copula C such that*

$$F(x_1, \cdots, x_d) = C(F_1(x_1), \cdots, F_d(x_d)) \tag{5}$$

If X is continuous, then such a copula C is unique. Conversely, if we know the joint cumulative distribution junction F and the marginals $F_1, \cdots, F_d$, *we can find the copula via*

$$C(u_1, \cdots, u_d) = F(F_1^{-1}(u_1), \cdots, F_d^{-1}(u_d)) \tag{6}$$

where $F_j^{-1}(t) = \inf\{s : F_j(s) \geq t\}$.

Lemma 1 illustrates the existence of copula functions. For computing the weight of different marginal distributions, Kendall tau, one of the correlation measures of the copula function, is used in this section. The specific definition is given as

$$\xi = \Pr[(X_1 - X_2)(Y_1 - Y_2) > 0] - \Pr[(X_1 - X_2)(Y_1 - Y_2) < 0] \tag{7}$$

where (X_1, Y_1), (X_2, Y_2) are independent identically distributed binary random vectors.

The copula function used in this paper is Gaussian copula, which belongs to a family of elliptic copula function. The cumulative distribution function and probability density function are given below.

$$C(u, v; \rho) = \int_{-\infty}^{\psi^{-1}(u)} \int_{-\infty}^{\psi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(\frac{-r^2 - s^2 + 2\rho rs}{2 - 2\rho^2}\right) drds \tag{8}$$

$$p(u, v; \rho) = \frac{1}{\sqrt{1-\rho^2}} \exp\left(-\frac{\psi^{-1}(u)^2 + \psi^{-1}(v)^2 - 2\rho\psi^{-1}(u)\psi^{-1}(v)}{2 - 2\rho^2}\right) \exp\left(-\frac{\psi^{-1}(u)^2\psi^{-1}(v)^2}{2}\right) \tag{9}$$

where $\psi^{-1}(\cdot)$ is the inverse function of unary normal distribution, and ρ is the linear correlation coefficient.

According to the copula function above, the weight τ_i of the i variable used to obtain the proportion of correlation can be defined as

$$\tau_i = \frac{\xi_i}{\xi_1 + \cdots + \xi_n} \tag{10}$$

where n represents the number of variables.

To analyze the performance of dynamic systems, the data model can be expressed as

$$\rho_s(k) = \left[\, \rho^T(k) \cdots \rho^T(k+s) \,\right]^T \tag{11}$$

where k stands for the instant,s is the stacked size. It is worth to mention that ρ can represent any variables in systems. Therefore, the data-driven observer based on deep learning technology for dynamic systems can be constructed by full connection neural network as follows:

$$\mathcal{NN} = \min \sum_{k=s+1}^{N-s} \frac{1}{2} \left\| y_s(k) - \mathcal{A}\begin{pmatrix} u_{s-1}(k-s) \\ u_s(k) \quad ; \; \Theta \\ y_{s-1}(k-s) \end{pmatrix} \right\|_2^2 \tag{12}$$

According to the setting of network model above, the observer can be defined as

$$\hat{y}(k) = \mathcal{A}(u(k); \Theta) \tag{13}$$

Based on (8) and (11), the joint data-driven observer for traction systems can be obtained as

$$\hat{y}_{\_joint}(k) = \frac{1}{n} \sum_{i=1}^{n} \tau_i \hat{y}_i(k) \tag{14}$$

where $\hat{y}\_{joint}$ represents the estimation of joint observer output. Fault detection can be accomplished by errors below.

$$e\_{joint}(k) = y\_{joint}(k) - \hat{y}\_{joint}(k) \tag{15}$$

2.3 Implementation Procedures of Fault Detection

Following the proposed fault detection method in this study, the implementation procedure is formulated in Algorithm 1.

Algorithm 1 Fault detection using joint observer
1: Load the normal data of y_i and fault data y_i^f
2: Calculate the copula function by (6) and obtain the Kendall tau by (7)
3: Calculate the joint weight by (10)
4: Construct the data-driven observer by (12)
5: Estimate the joint output of systems by (14)
6: Detect the fault by using errors in (15)

3 Verifications

For illustrating the practicality of the proposed method, two different experiments developed by traction systems are designed. Then, the experimental environment and experimental results are given below.

3.1 Experiment on Pilot-Scale Platform

The traction systems shown in Fig. 2 contains the cabinet, the traction motor, and sensors. The input voltage is 220V and the power of module is 10KW. The parameters of traction systems in this experiment are given in Table 1. Figure 3(a) illustrates the probability density function of copula. It is different with the Archimedean copula function because of the symmetric tail correlation. Figure 3(b) shows the fault detection result using the proposed method. The system fault is happened in the 100th sample. When the fault occurs, the residual has a significant step.

3.2 Verification on Traction Systems of High-Speed Trains

For illustrating the practicality, the proposed method is verified by the running data of traction system in high-speed trains. The traction motor equipped in trains is shown in Fig. 4. All the running data are collected from monitoring systems in high-speed trains. Figure 5(a) illustrates the probability density function of copula for actual data. It also has symmetric tail correlation. Figure 5(b) shows the fault detection result using the running data of train system. The system fault happened in the 35th sample. Although, due to the complexity of the actual systems, false alarm appears at the 9th and 13th sample points, the results of fault detection are still satisfactory.

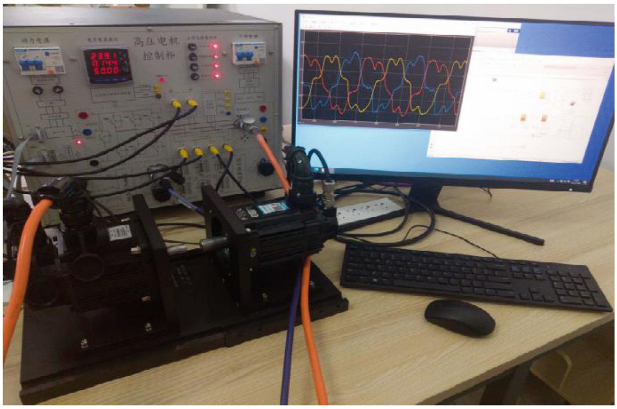
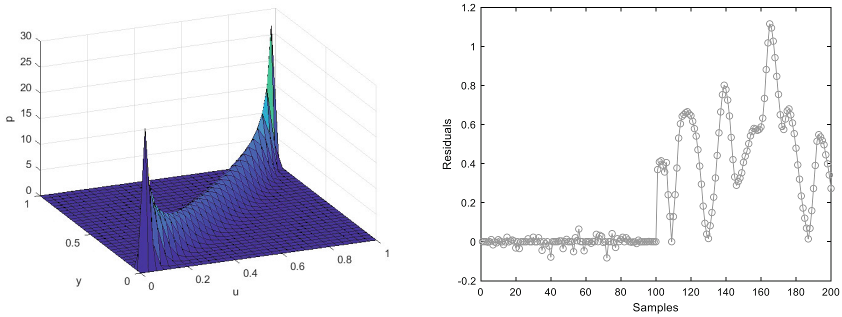


Fig. 2. Traction control systems in laboratory

Table 1. Parameters of motor

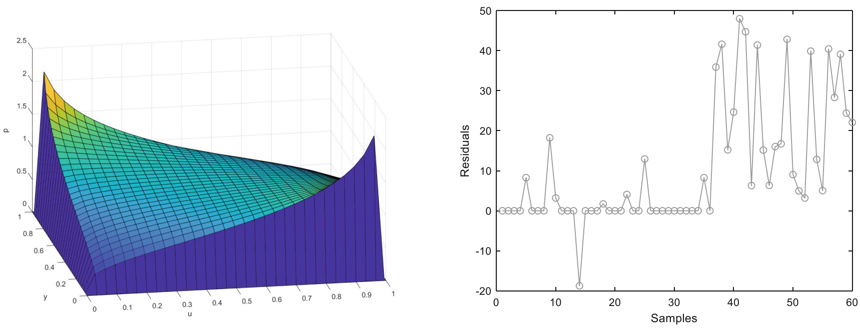
Parameter	Value	Parameter	Value
Mechanical time constant	4.989 ms	Power	0.6 KW
Rated torque	2 NM	Electrical time constant	2.968 ms
Rated speed	3000 RPM	Torque constant	0.5 Nm/Arms
Rated current	4 A	Maximum current	12A
Rotor inertia	0.425	Maximum torque	6 NM



(a) Probability density function of copula (b) Detection result of motor fault

Fig. 3. Experimental results of traction control systems in laboratory

Fig. 4. Traction systems of high-speed trains



(a) Probability density function of copula (b) Detection result of motor fault

Fig. 5. Experimental results of traction control systems in high-speed trains

4 Discussions

Although data-driven fault detection technology has some limitations in its current development stage, it still has significant potential for industrial systems. Especially for multi-sensor monitoring systems, the observer-based modeling approach can describe the system's dynamic behavior and directly construct residual generators to detect faults. Most importantly, when sufficient data is available, data-driven methods can greatly reduce modeling complexity and achieve satisfactory detection results. However, for the traction system of high-speed trains, there are still some issues that need further consideration:

(1) In engineering applications, the real-time performance of algorithms is always a hot topic. How to further improve the computing efficiency of high frequency sampling systems deserves more attention.
(2) While nonlinear observer models are effective in describing system characteristics, the design of such models for distributed systems poses significant challenges.

(3) Besides the characteristics of initial variables, the correlation between process variables and noise should be considered.

5 Conclusions

In this article, a data-driven joint observer is proposed for traction systems in high-speed trains. To obtain the joint distribution of system state, marginal distributions of all variables are considered in this scheme. In the end, the proposed method is verified by different experiments. Results shows the superiority of this method. Benefiting from the joint model, future research consists of fault configuration and health prediction for other complex systems is possible.

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