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AN SFA–HMM PERFORMANCE EVALUATION METHOD USING STATE DIFFERENCE OPTIMIZATION FOR RUNNING GEAR SYSTEMS IN HIGH–SPEED TRAINS

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The evaluation of system performance plays an increasingly important role in the reliability analysis of cyber-physical systems. Factors of external instability affect the evaluation results in complex systems. Taking the running gear in high-speed trains as an example, its complex operating environment is the most critical factor affecting the performance evaluation design. In order to optimize the evaluation while improving accuracy, this paper develops a performance evaluation method based on slow feature analysis and a hidden Markov model (SFA-HMM). The utilization of SFA can screen out the slowest features as HMM inputs, based on which a new HMM is established for performance evaluation of running gear systems. In addition to directly classical performance evaluation for running gear systems of high-speed trains, the slow feature statistic is proposed to detect the difference in the system state through test data, and then eliminate the error evaluation of the HMM in the stable state. In addition, indicator planning and status classification of the data are performed through historical information and expert knowledge. Finally, a case study of the running gear system in high-speed trains is discussed. After comparison, the result shows that the proposed method can enhance evaluation performance.

Keywords: slow feature analysis (SFA), performance evaluation, hidden Markov model (HMM), running gear systems.

1. Introduction

For complex cyber-physical systems, the safety and reliability of high-speed trains are the first factor be considered in operation (Song *et al.*, 2021; 2020). Also, as the running time increases, the damage to high-speed trains is aggravated by the harsh environment and overload (Chen and Jiang, 2020). It is necessary to accurately capture the health status of systems. The running gear system is the crucial part in high-speed trains, and its reflected states have an important impact on the whole performance. The performance evaluation of running gear systems in high-speed trains is studied in this paper.

Performance evaluation plays a central role in performance degradation or failures that may occur in the process of real-time monitoring and diagnosis. Current performance evaluation has developed from the initial control loop to the process level or an even larger scale, and the specific evaluation procedure is more complex (Kaczorek and Ruszewski, 2022). There are many quantitative and qualitative methods proposed for the performance evaluation of systems (Zhang *et al.*, 2021; Salazar *et al.*, 2020). The qualitative empirical method uses incomplete prior knowledge to describe the

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functional structure of systems to obtain a qualitative model. Its structure includes empirical reasoning and qualitative behavior prediction and comparison. By comparing the predicted system behavior with the actual behavior, we can determine whether a failure occurs (Yan *et al*., 2017; Zheng *et al*., 2019). Moreover, the empirical method obtains the information of target cases based on case-based pattern classification or causal relationships between variables (Cheng *et al*., 2021). High-speed train control systems are indispensable for ensuring operation safety, but qualitative empirical methods are gradually unable to meet the accuracy requirements for evaluation. Data-driven methods began to be the core in the field of performance evaluation (Chen *et al.*, 2022; Luo *et al.*, 2018; 2020). According to different data-processing modes, data-driven methods are divided into several categories. Quantitative methods include artificial intelligence methods (Kiranyaz *et al*., 2018; Yuan *et al*., 2020), signal processing methods (Li *et al*., 2018) and statistical analysis methods (Wang *et al*., 2020). Artificial intelligence methods include artificial neural networks, fuzzy mathematics, genetic algorithms, etc. Signal processing methods mainly cover empirical mode decomposition. In addition, statistical analysis methods include principal component analysis (PCA) and Bayesian theory, etc.

Relying on incomplete experience, empirical modeling techniques still cannot achieve the stringent accuracy requirements for performance evaluation. In recent years, the performance evaluation of systems has focused on classification and statistical methods, which take mathematical statistical analysis or a historical empirical training model as the main structure, such as the HMM, the support vector machine (SVM), and PCA (Deng *et al*., 2018). Due to the shortcomings in the physical meaning of the traditional PCA assessment results, Liu *et al.* (2013b) proposed a performance grade classification and identification method based on data modeling. PCA is developed to improve the identification and yield the best performance level. Zou and Zhao (2019) proposed a performance evaluation method based on hierarchical cointegration analysis. By adjusting the stationarity and non-stationarity of data evaluation, a global model is built for evaluation. Similarly, for systems in high-speed trains, the availability and reliability of the system can be determined by the calculation of model parameters or relevant-variable selection (Liu *et al*., 2013a; Yun *et al*., 2017; Jiang *et al*., 2020). Also, Markov modeling ideas are proposed to be used in the performance evaluation of train systems (Molaei *et al*., 2007). Sun *et al*. (2020) used wavelet decomposition to obtain attitude monitoring index vectors. Combined with the application of the HMM and genetic algorithms, the method converged to a local optimal value, thereby improving performance and obtaining a higher average recognition rate. The above-mentioned methods lack analysis of the system mechanism and status, and in order to make the research on the influencing factors and evaluation indicators of characteristic data clear, the proposed method considered the quantitative part. For the quantitative mathematical model with a precise process, performance evaluation can be carried out by constructing physical models and mathematical model analysis. Yan *et al*. (2015) combined the intrinsic mode function energy entropy with the relevant dimensions of chaos theory. By utilizing the function energy entropy and relevant dimensions, dynamic changes with different metrics are reflected.

Compared with the previous algorithm, the accuracy of evaluation has been increased, but this kind of model lacks a combination of actual physical meaning when targeting specific industrial processes. Similarly, recent efforts in performance evaluation pay more attention to the amelioration and fusion of traditional methods (Chen *et al*., 2018; Zhang *et al*., 2018). For instance, Bui *et al*. (2016) used the information gain ratio of feature selection to compare various state evaluation methods. Then they pointed out that there are still deficiencies in the evaluation of support vector machines. To improve the accuracy of classification, a semi-supervised support vector machine method is proposed. By using the k-means technique to label data clusters, a specific differentiable surrogate of the loss function is developed to achieve the optimization effect (Wang *et al*., 2017). Don and Khan (2019) proposed to use a hybrid system consisting of a hidden Markov model a Bayesian network to detect the abnormal in-process data while evaluating the log-likelihood. With the combination of statistical analysis and a classification evaluation model, better results are obtained (Zhang and Zhao, 2019; Wu *et al*., 2017; Chen *et al*., 2021). Shang *et al*. (2015) proposed a new process monitoring strategy based on SFA to monitor process dynamic abnormalities, where the s^2 statistic of SFA shows the potential changes of system states. Since the slow function of latent variables can describe the dynamics of slow changes, interpretability has been improved. In view of the fact that the proposed statistic can detect the health status of the system process, this paper proposes a health performance evaluation model based on SFA and difference optimization in the state. It is of great importance for the performance level of a complex system. Thus, the accuracy of the evaluation can be improved by controlling the influence of disturbance factors.

In this paper, a health assessment method based on SFA and state transition optimization is developed as well as applied to running gear systems in high-speed trains. Through the extraction of slow features in the data, the method analyzed probability transitions and adjusted expectations. With the parameter identification, a detailed performance assessment is provided. The paper combines SFA with the HMM, and makes an in-depth analysis of feature variables in running gear systems. Thus, it can reflect the evaluation performance of running gear systems in high-speed trains.

The rest of this paper is organized as follows. Section 2 briefly reviews the HMM and SFA methods. Section 3 introduces the proposed model and the optimization scheme of slow feature entropy analysis for evaluation performance. Based on this, the mechanism analysis and problem description of high-speed train running gear systems are carried out. In Section 4, the method is applied in the running gear system, and the simulation analysis proves its feasibility. Moreover, it is compared with other methods to illustrate the effectiveness. Finally, Section 5 contains a summary of this paper.

2. Preliminaries

Based on the SFA-HMM method using state difference optimization, this paper studies the performance evaluation for running gear systems. In the initial part of the proposed method, the fusion of SFA and the HMM is mainly used for feature extraction and preliminary evaluation. This section briefly characterizes SFA and the HMM.

2.1. Slow feature analysis.

For high-speed trains, multiple features need to be reduced dimensionally, which can increase the accuracy of the evaluation. Data reflecting the change trend of the high-speed train running gear system are characterized by random noise and interference, which seriously affects the accuracy of the assessment results. SFA is the most effective way to reduce noise and interference. In this part, SFA is used to analyze the slowness of data in achieving the purpose of dimensionality reduction.

As a popular unsupervised method, SFA can extract slowly changing latent variables (LVs) from data. For a multi-dimensional input signal, the goal of SFA is to find an input-output mapping function in which the output signal changes as slowly as possible. LVs of output signals will carry the major information if the time structure is shown in the input data (Shang *et al.*, 2015).

Mathematically, the SFA optimization problem is defined as follows:

$$s = Wx. \tag{1}$$

In SFA, the main purpose is to find a matrix $W = \begin{bmatrix} w_1 & w_2 & \cdots & w_m \end{bmatrix}$ to represent the coefficient vector under the following conditions:

$$\langle s_j \rangle_t = 0, \tag{2}$$

$$\langle s_j^2 \rangle_t = 1, \tag{3}$$

$$\forall i \neq j : \quad \langle s_i s_j \rangle_t = 0. \tag{4}$$

The variance and correlation are processed above, in which $\{s_j(t) = w_j(x(t))\}_j^m$, $x(t) = [x_1(t), \dots, x_m(t)]$, and $\langle \cdot \rangle_t$ denotes temporal averaging.

After singular value decomposition (SVD), the matrix can be described by

$$\langle xx^T \rangle_t = U \Lambda U^T \tag{5}$$

and then the whitening transformation is obtained after preprocessing

$$z = \Lambda^{-\frac{1}{2}} U^T x = Qx, \tag{6}$$

where $Q = \Lambda^{-\frac{1}{2}} U^T$. Note that

$$\langle zz^T \rangle_t = Q \langle xx^T \rangle_t Q^T = I. \tag{7}$$

The acquisition of the coefficient vector-matrix translates into finding the matrix P in

$$S = Pz = PQx, \quad P = WQ^{-1}. \tag{8}$$

The second SVD of the matrix $\langle \dot{z}\dot{z}^T \rangle_t$ is expressed as

$$\langle \dot{z}\dot{z}^T \rangle_t = P^T \Omega P. \tag{9}$$

Therefore, the optimal solution can be regarded as singular values in the ascending order of the matrix Ω. Based on the coefficient matrix, one can obtain the variables with slow features. For getting the best option to reflect the essential characteristics, this paper selects two columns of data in the slowest change.

2.2. Hidden Markov model.

As a statistical model, the HMM describes Markov processes with implicit unknown parameters, and one is suitable for the evaluation part of this paper. By using the theory of probability distributions, this method completes the training and evaluation of the feature data.

The HMM is represented by a triple as $\lambda = (\pi, A, B)$, where π is the initial probability distribution vector, A is the state transition probability matrix, B is the observation probability matrix, N is the number of states in the model; M is the maximum number of observations corresponding to each state, o_t represents the observed value at the time t, $o_t \epsilon \{V_1, V_2, \dots, V_M\}$.

In the following, two general assumptions are used:

A1. *Markov property hypothesis:* At any time t, the state of a hidden Markov chain depends only on the previous state. However, it has nothing to do with the state or observations at any other moment.

A2. *Observation independence hypothesis:* The observation at any time depends on the status of the Markov chain at that time. Conversely, it has nothing to do with other observations or states.

First, the method needs to obtain the output probability $P(O|\lambda)$ under some conditions. For the solution of the output probability, the forward initial variable and the backward initial variable are denoted respectively as $\alpha_t(i)$ and $\beta_t(i)$. If the model is λ, $\alpha_t(i)$ is the probability of the observation O until the time t, $\beta_t(i)$ is the probability of the observation O from the time $t+1$. Setting the state at the time t as H_i, according to the forward and backward probabilities, the observed sequence probability is written as

$$P(O|\lambda) = \sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j), \quad t = 1, 2, \ldots, T-1. \tag{10}$$

The Viterbi algorithm is a progressive search algorithm that is applied to find an optimal state sequence in the HMM. For the given model parameters and observation sequence, the Viterbi algorithm can obtain the target state sequence. The recurrence relationship and auxiliary variables are defined in (11)–(15).

The optimal state sequence for a given partial observation sequence $q_1, \ldots, q_t$, $\delta_t(i)$ is defined as

$$\delta_t(i) = \max_{q_1,\ldots,q_{t-1}} P(q_1, \ldots, q_t, q_t = H_i, o|\lambda). \tag{11}$$

The initialization of $\delta_t(i)$ is defined as follows:

$$\delta_1(i) = \pi b_i(O_1). \tag{12}$$

After simple derivations, the result is

$$\delta_{t+1}(i) = \max_{N \geq j \geq 1} [\delta_{t-1}(j) a_{ji}] b_i(O_{t+1}). \tag{13}$$

The optimal path can be calculated with

$$P^* = \max_{1 \leq j \leq N} \delta_T(i), \tag{14}$$

$$q^* = \arg \max_{1 \leq j \leq N} \delta_T(i). \tag{15}$$

One can get variables when the function is maximized (the optimal path).

In the next step, the algorithm can find the appropriate model parameters to maximize $P(O|\lambda)$. The maximum likelihood estimation solution is as follows: concerning the target log-likelihood function P, the EM algorithm is used for the function

$$Q(\lambda, \tilde{\lambda}) = \sum \log P(O, I|\lambda) p(O, I|\tilde{\lambda}) \tag{16}$$

and then model parameters are obtained by the Lagrange solution.

In the part of HMM re-evaluation, by maximizing the output probability $P(O|\lambda)$, the model λ is trained and defined as

$$\xi_t(i,j) = P(q_t = H_i, q_{t+1} = H_j|O, \lambda), \tag{17}$$

$$r_t(i) = P(q_t = H_i|O, \lambda), \tag{18}$$

$$H(\lambda, \bar{\lambda}) = \sum_{Q} \log P(O, O|\bar{\lambda}) P(Q, O|\lambda). \tag{19}$$

With the analysis of the relationship between $\alpha_t(i)$ and $\beta_t(i)$, the initial model parameters are adjusted according to the training rules. By constructing the auxiliary function to get $\bar{\pi}_i, \bar{\alpha}_{ij}, \bar{\beta}_j(k)$, $\bar{\lambda}$ is re-derived as an optimal solution. The whole process completes the procedure of training and evaluating the feature data.

3. Health state assessment model based on optimization of state difference

Concerning the robustness and accuracy of the evaluation model, the health evaluation model can be achieved based on the following four steps: data extraction and dimensionality reduction, feature extraction, health evaluation, and optimization. Figure 1 shows the block diagram of the evaluation system proposed in this article.

3.1. SFMEA (slow feature maximum entropy analysis)–HMM. Based on the dynamic characteristic

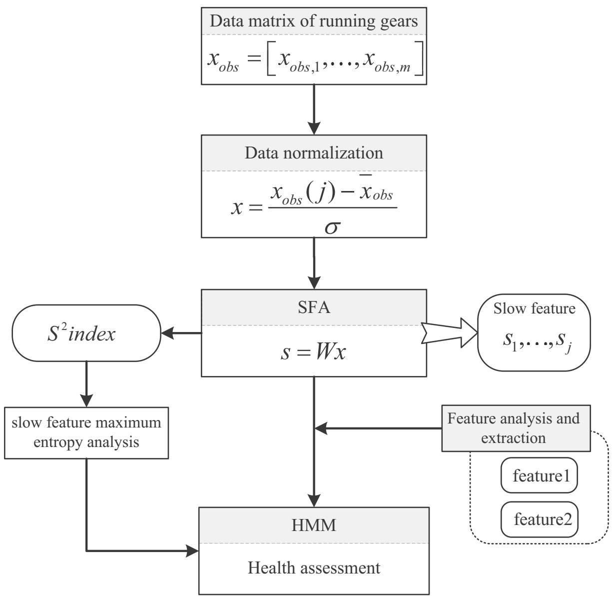


Fig. 1. Health assessment model.

of SFA, the stability of the data and the operating conditions are analyzed. At the same time, combined with the analysis of potential anomalies in dynamics, the paper finds that the stability deviation can infer the differences between system states and further optimize the evaluation model. To reduce the error of the evaluation result, this subsection uses the slow feature to process the data and design the monitoring optimization module. Then, the HMM is used to evaluate and analyze the state difference reflected in the slow feature detection.

After the basic calculation of SFA, slow features can be obtained in the form of

$$s = [s_1, \dots, s_{m(d+1)}] = [s_d^T, s_e^T], \tag{20}$$

where s_d is the principal part and s_e is the residual part.

To get potential abnormalities in process dynamics, the control limit is set as

$$s^2 = \dot{s}_d^T \Omega_d^{-1} \dot{s}_d, \tag{21}$$

$$s^2 \sim g F_{M,N-M-1}, \tag{22}$$

where

$$g = \frac{M(N^2 - 2N)}{(N-1)(N-M-1)}, \tag{23}$$

in which, $\dot{s}$ represents the first derivative of LV with respect to time.

SFA processes the monitoring data preliminarily based on a statistical threshold, and above the thresholds are sieved to reduce interference items. Further, the effective range of change is selected as the final goal of entropy analysis to mitigate misjudgments. After comparing the simulation results, this paper selects three adjacent values sequentially as sub-arrays (sub-array: $c_i = [s_i, s_{i+1}, s_{i+2}]$, $i = 1, \dots, n-2$) and calculated their average value. By arranging the obtained means in descending order, the algorithm retains the position information and performs the entropy analysis in the next step.

Based on the influence of data perturbation, invalid destabilizations and undetermined disturbance are two kinds of disturbances in the S^2 process monitoring, in which the former cannot reflect changes in the running status, and the latter has an impact on state changes but does not belong to the effective range of changes. To optimize the state evaluation, this paper uses the maximum entropy model to analyze the probability characteristics of the results. In this part, the effective range that can show that the state transition is obtained. The specific steps are described in Algorithm 2.

The entropy analysis of conditional probability is described in

$$\min_{P \in C} H(P) = \Sigma_{x,y} \tilde{P}(x) P(y|x) \log P(y|x) \tag{24}$$

subject to

$$E_P(f_i) - E_{\tilde{P}}(f_i) = 0, \tag{25}$$

$$\sum_y P(y|x) = 1, \tag{26}$$

where C is the set of models satisfying the constraints. About the characteristic function, the expected value for the empirical distribution is equal to the expected value for $P(Y|X)$.

In (26), $E_{\tilde{P}}(f)$ is the expected value for the empirical distribution, $E_P(f)$ is the expected value for $P(Y|X)$.

Based on the Lagrange multiplier $(\omega_0, \omega_1, \dots, \omega_n)$, $L(P, \omega)$ is defined as

$$\begin{aligned} L(P,\omega) &= -H(P) + \omega_0(1 - \Sigma_y P(y|x)) \\ &\quad + \sum_{i=1}^{n} \omega_i (E_p(f_i) - E_{\tilde{P}}(f_i)). \end{aligned} \tag{27}$$

The dual transformation of optimization is defined by $\max_\omega \min_{P \in C} L(P, \omega)$. For minimization problems, it is solved via

$$\frac{\partial L(P,\omega)}{\partial P(y|x)} = 0. \tag{28}$$

The dual external maximization problem can be solved as follows:

$$\omega^* = \arg\max_\omega \psi(\omega). \tag{29}$$

Algorithm 1. Solving for sub-arrays.

Input: $feature$ (slow features); $S^2 - index$ (threshold of test statistics).

Output: Y (the array in descending order); I (located information of C).

Step 1. Process the measurement data. Set $i = 1$; If $feature(i) > S^2 - index$, set $data(i) = feature(i)$; otherwise $data(i) = 0$, set $i = i + 1$ and go back to Step 1.

Step 2. Define sub-array C and obtain the means.

Step 3. Sort the obtained means in descending order.

Algorithm 2. Optimization evaluation of SFMEA.

Input: $feature$ (slow features); I (located information of C).

Output: optimization of evaluation results.

Step 1. Define the constraint function of the maximum entropy analysis model. Set part of the data to 1, and the rest to 0.

Step 2. Train and obtain optimal results of the evaluation.

Step 3. Optimize the part of the stationary interval and retain the undetermined disturbance.

The definition of the feature function needs to consider the health characteristics reflected by the slow feature data.

3.2. Construction of running gear systems in a high-speed train performance evaluation model. Due to the high complexity of high-speed trains, the health status of its subsystems must be grasped accurately to protect the passengers' personal and property safety (Chen *et al*., 2020). As one of the key components of high-speed trains, the running gear system exhibits a mechanical performance that makes a direct impact on the overall fault status detection.

3.2.1. Mechanism analysis in running gear systems. The main task of the high-speed train running gear system is to guide the vehicle to run flexibly, safely, and smoothly along the rail under the action of traction power. Figure 2 shows the structure of the running gear. The running gear system consists of wheelsets, bogies (side frames and bolsters), spring damping devices, and braking devices.

Bogie technology's structure and performance directly affect the power, stability, and comfort of the vehicle. The multi-component cooperation of the bogie system has five operation statuses, i.e., traction, braking, steering, load-bearing, and buffering. To ensure the normal operation of the vehicle, the status assessment of the running gear system is particularly important.

In view of the vibration and shock caused by various reasons during the running of the rail vehicle, the vibration damping device is composed of a shock absorber and a spring. In the vibration damping device, the spring mainly serves as a buffer to alleviate the impact and vibration of the track. The function of the shock absorber is to reduce vibration, and its force is always opposite to the direction of motion, which plays a role in preventing vibration.

A performance characteristic is the representation of the system state (Jiang and Yin, 2019). Based on the factors affecting the status of the running gear system in high-speed trains, this paper analyzes the working principle of each component of the running gear. Then it can be seen that temperature changes are accompanied by changes in component performance. For spring devices, the relationship between the hardness correction coefficient and temperature (t) is shown in Fig. 3(a). As the temperature increases, the hardness correction coefficient decreases; as the temperature decreases, the hardness correction coefficient increases. Regarding the principle of the shock absorber operation, Fig. 3(b) shows the relationship between resistance and vibration speed. The performance of the shock absorber affects the control and cushioning of the vibration and the impact in the running gear system. Accordingly, this paper reasonably concludes that changes in the health status will also have different representations of temperature, vibration, and impact data. Thus, the temperature, impact, and vibration are selected as the data characteristics of performance evaluation.

After a detailed analysis of running gear systems in high-speed trains, this paper proposes a performance evaluation model of running gear systems based on the SFM-HMM. Given the data analysis of the running gear system, the following four problems are solved:

(i) Combined with the mechanism analysis of the high-speed train running gear, the characteristic points that affect the high-speed train running gear are analyzed to select the data measurement point. To extract slow features from the rapidly changing signal, this paper extracts tiny changes in pre-analysis data. The slowest features are selected after further dimensionality reduction.

(ii) For the extracted slow features, further processing is performed for feature selection. According to the function of refining features based on SFA, a correlation fitting function is introduced to match the original data with the slowest data to complete the feature selection.

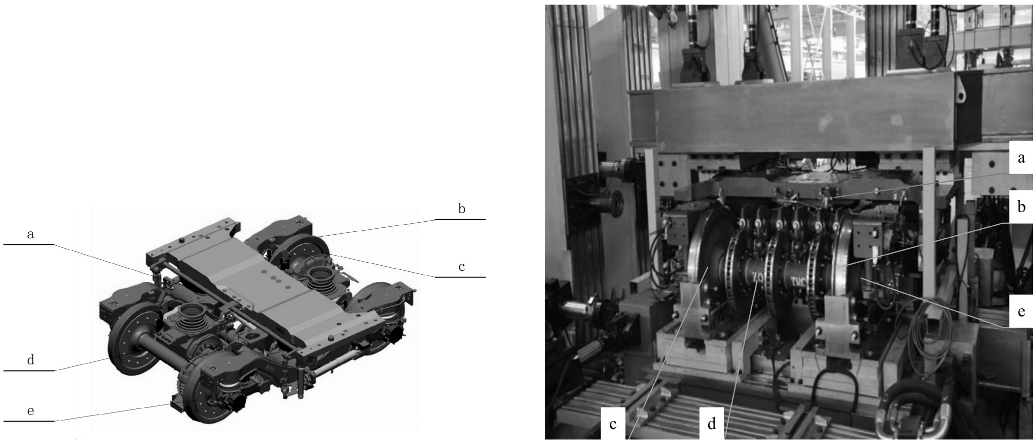
(iii) After performing the status classification of the data through historical information and expert experience, a hidden Markov health evaluation model is established to evaluate the status of the running gear system in high-speed trains.

(iv) SFMEA is proposed to analyze the data difference in state changes, then further describe the evaluation model and arrive at the optimization.

3.2.2. Data preprocessing. Aiming at the status assessment of running gear systems in high-speed trains, its particularity concerns mainly the need to consider the horizontal characteristics and the longitudinal trend of the operating data. The characteristics of the running gear system are complex and diverse, so the data distribution has a certain particularity. The data collected in the actual operation of high-speed trains contains disturbances, so the input data needs to be analyzed and pre-processed.

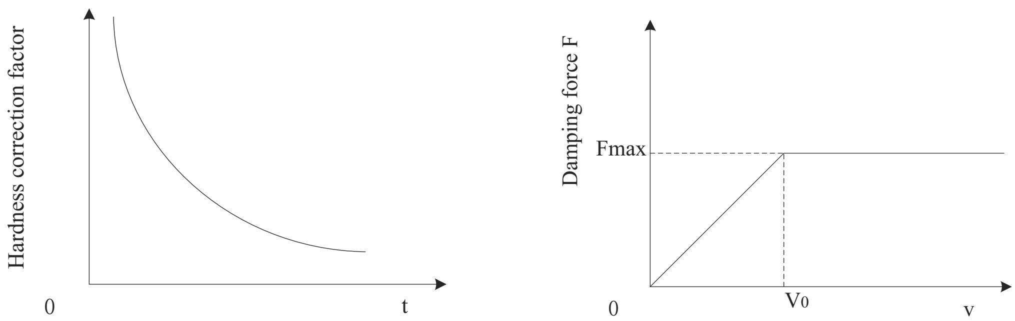
The running gear system possesses many sensors to monitor the status of the running gear system. The sensors are integrated with multiple sensor units to monitor different physical quantities and collect various types of data, such as temperature, vibrations, and impact.

To truly reflect the health status of high-speed trains, the data collected by multi-source sensors are preprocessed. This is called data normalization, including two steps.



(a) (b)

Fig. 2. Structure chart of high-speed train running gear systems: truck frame (a), wheel (b), brake (c), trailer axle (d), absorber (e).



(a) (b)

Fig. 3. Relationship between the correlation index and temperature vibration characteristics.

Step 1:

$$\overline{x}_{\mathrm{obs},l} = \frac{1}{N}\sum_{j=1}^{N}(x_{\mathrm{obs},i}(j) - \overline{x}_{\mathrm{obs},l})^2. \tag{30}$$

For measurement data from multiple sensors, the m-dimensional process vector, which is denoted by x, forms a measurement data matrix. Considering the change in the average value of the measurement vector, this paper adopts correlation-based preprocessing. Hence each column of measured variables subtracts the corresponding variable mean and divides the corresponding variable by its standard deviation. Thus, a variable with unit variances and zero means is obtained.

Step 2:

$$x(k) = \begin{bmatrix} \dfrac{x_{\mathrm{obs},i}(j) - \overline{x}_{\mathrm{obs},l}}{\sigma_{\mathrm{obs},1}} \\ \vdots \\ \dfrac{x_{\mathrm{obs},i}(j) - \overline{x}_{\mathrm{obs},l}}{\sigma_{\mathrm{obs},m}} \end{bmatrix},$$

$$(X = [x(1), \dots, x(N)] \in \mathbb{R}^{m\times N}). \tag{31}$$

3.2.3. Problem description: Pre-defined indicators and evaluation model construction. Based on a large amount of historical data from high-speed trains, taking into account expert knowledge, this case uses temperature, vibration, and impact as the data characteristics to estimate the state of the running gear system in high-speed trains. Since actual data measurement is difficult, in this paper data for the same train with the trend of increasing mileage in nearly a month for analysis are selected. To ensure the validity and accuracy of input data, the multi-point sampling method is used for data collection. According to the division of the sensor position in the high-speed train running gear, six total types of characteristic data are set at two sampling points, as well as data denoising. Reference values are designed using expert knowledge and actual conditions of a high-speed train running gear, i.e., the reflection of vibration and temperature variables on performance changes shows a direct correlation with data fluctuations, the impact data makes an immediate influence on the data burst.

In traditional engineering, the health states of systems are mainly divided into normal, sub-health, and failure. Based on the existing form, this paper further divides these into two parts: a sub-health status and an under-fault status. When the temperature is no more than 20 degrees, the vibration is no more than 16, the data is in a healthy state, the temperature is no less than 40 degrees, and the vibration is no less than 25, the data is in a fault state. Conveniently for the construction of the model, it is necessary to establish a priority based on the historical experience of the travel department system. Based on the analysis of the historical fault information, by comparing with the other two features, the impact priority is set to the lowest level because it has little effect on the change in the system performance state. To reflect the actual working conditions as comprehensively as possible, the approach function is set according to the existing standards, and the preliminary classification settings are performed in a recycle selection mode. Consequently, to attain an optimal performance of the controlled running gear system, the performance evaluation is divided into the following states: health, sub-health, under-fault, and fault. Their interpretations are as follows:

- health: the overall performance of the running gear system is intact;
- sub-health: components are worn, which has a slight impact on the performance of the running gear system and the impact is still in the controllable range;
- under fault: the components of the running gear system are seriously worn, which moderately affects the performance and needs to be handled in time;
- fault: the component is damaged or nearly damaged, which seriously affects the train performance and needs fault handling.

Because of the multiple features selected in this article, it is necessary to reduce the dimension of original data, and the slowest changes in the extracted are retained for further feature selection.

The proposed method uses characteristics of the evaluation status as evaluation criteria, and the HMM is chosen to complete the training and evaluation of the data. After feature selection, the training model can yield preliminary evaluation results. Performing characteristic analysis on the slow feature data, the evaluation model is optimized according to the state difference characteristics to obtain more accurate results.

The monitoring result of the threshold by SFA on the test data of the running gear system is shown in Fig. 4. The s^2 evaluation standard indicates the potential abnormality of the system state. When the system state changes, for the four states defined in this paper, the detection results may reveal obvious fluctuations.

In the part of SFMEA, the crucial information is extracted according to the health state characteristics reflected by SFs, and the maximum entropy feature function is defined as

$$f(x,y) = \begin{cases} 1 & \text{if the first 30 numbers are} \\ & \text{in descending order,} \\ 0 & \text{otherwise.} \end{cases} \tag{32}$$

Thus, the position sorting information is used to select the first 30 data pieces to set the constraint feature function of the maximum entropy. Then the analysis of the maximum entropy estimation with each sub-array as the center is obtained. In Fig. 5, at the part of ME1, the algorithm selects the best three data intervals for the analysis results, i.e., the optimized region solution that removes redundancy. To achieve effective optimization, the independent redundant point is set as the undetermined disturbance (optimized blank processing) in the ME2 section shown in the figure, and the state evaluation result of the optimization interval is defined. Through the functional assessment and the optimization model, the proposed method is integrated with the monitoring module. In the state of the obtained model, the maintenance module further adjusts and repairs the running gear system through the management personnel.

3.2.4. Feature selection. Six data sets based on temperature, vibration, and impact need further feature extraction. Different from PCA, the data processing structure of SFA includes whitening and SVD on the time derivative. The structure is complex and the main features cannot be expressed through direct formula analysis.

This study uses the form of the fitting function to analyze the slowest features of the two groups and make the correlation test with original features. Figure 6 shows the steps of the entire feature extraction procedure.

A smooth function is selected to obtain the two sets of features through the highest correlation. Table 1 lists the correlation between the original features and the two groups of slowest features based on the analysis. Here, sf_2 and sf_1 represent the slowest features of the two groups. This paper takes the sum of squares due to error (SSE), root mean squared error (RMSE), and R-square as the standard correlation parameters. A larger R-square

Table 1. Related parameter results.

Goodness of fit	x_a, sf_1	x_b, sf_1	x_a, sf_2	x_b, sf_2
SSE	735.7	648.4	2.034	10.36
R-square	0.0939	0.2015	0.9975	0.9872
Adjusted R-square	0.0666	0.1779	0.9974	0.9869
RMSE	0.9661	0.9067	0.0508	0.1146

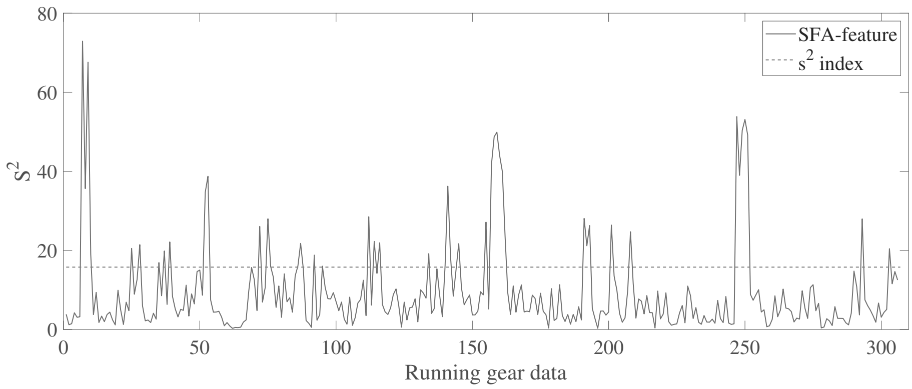


Fig. 4. Monitoring the influence of the threshold by SFA.

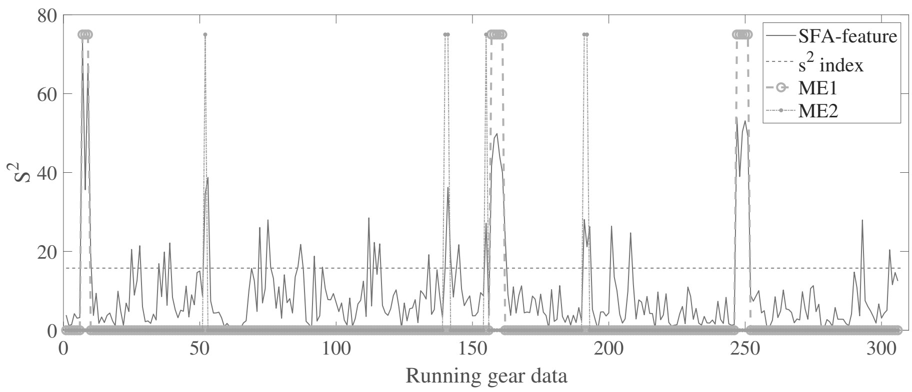


Fig. 5. Results of maximum entropy.

and a smaller SSE and RMSE indicate a higher correlation degree. From this, analyzing the correlation with the slowest features, two target features are found.

4. Case-study simulations and comparisons

Based on monitoring information on high-speed train operation by CRRC Changchun Railway Vehicles Co., Ltd., a monitoring signal generated by sensors under a set state of train operation is obtained. According to the above principles, the resulting effective feature is selected and extracted. The visualization of the modeling and simulation analysis of the proposed method is completed using the MATLAB simulation software.

4.1. Case-study analysis. Based on the necessity and usefulness of the health assessment of running gear systems in high-speed trains, a performance evaluation model based on the SFA-HMM is proposed. To verify the accuracy of the model, data from the running gear system in high-speed trains are used. Figure 9 shows the sensor position of the measured data. After analyzing the performance of the running gear system, this paper sets the index of the health evaluation. According to performance indicators, Fig. 7 shows the trend of actual monitored data. Due to the complexity of the real environment and the limitation of acquisition conditions, the data need to be denoised to reduce disturbances. Figure 8 presents a trend chart after data normalization.

As for data collection, the measuring point position of the running gear is shown in Fig. 9. To make the collected data fully show the features' state, data from eight positions of sensors are extracted in the figure. After stability and availability analysis of the data collected for each point, the data for positions A and B are selected as the input. To ensure the actual conditions, the monitoring data whose speed is not zero are selected as the simulation object from the original data.

In the next step, the data are processed through SFA, and the slowest two sets of features are obtained

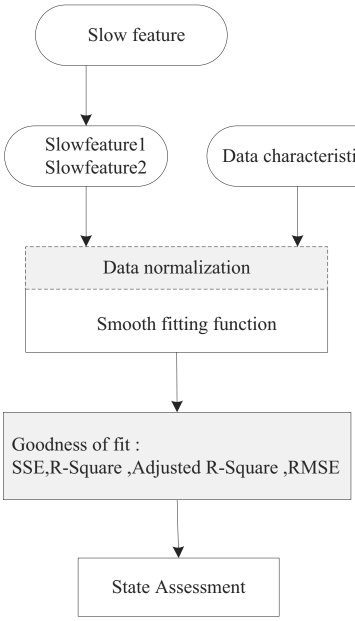


Fig. 6. Feature extraction.

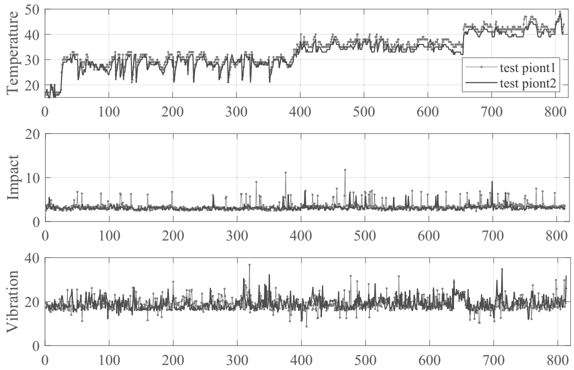


Fig. 7. Raw data.

by estimating the covariance matrix. Further, through the correlation analysis of slow features, the purpose of feature selection is achieved, which prepares the evaluation part.

4.2. Experimental analysis. The first 504 pieces of operation data are selected from the high-speed train as the training set of the HMM, and the training model meets the evaluation requirements. The evaluation results of the 309 test data are shown in Fig. 10, in which the open disks signify the evaluation result, the line is the correct status level; the second part of the figure shows the selected two sets of slow features. After SFMEA and optimization, the simulation results are shown in Fig. 11. The RMSE is used as the verification index. The RMSE of the proposed method model is measured and its value is 0.0455. In addition, the RMSE value of the optimized SFMEA method is 0.0130.

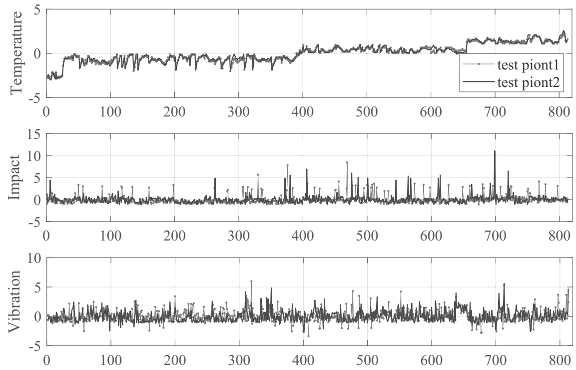


Fig. 8. Data normalization.

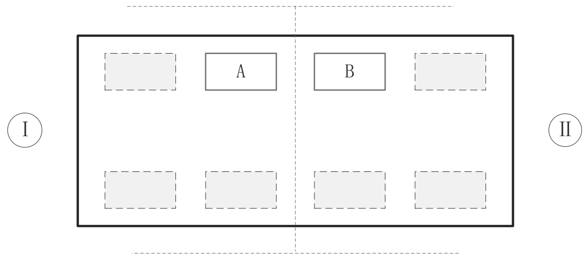


Fig. 9. Position of sensors for data acquisition.

Table 2. Results of the comparison.

Deviation	HMM	SVM	SFA-HMM	SFMEA-HMM
RMSE	0.0714	0.2110	0.0455	0.0130

4.3. Comparative analysis. To further illustrate the validity and accuracy of the model, two common health assessment methods, the HMM and SVM, are compared with the model method proposed in this article.

As shown in Fig. 12, the HMM is used for comparison with the model, and the evaluation results of the feature data are shown in the figure. After the calculation of the RMSE, the error value is 0.0714.

The SVM is a statistical analysis-based classification model like the HMM, and the researchers widely use it as the main model and contrast of the fault diagnosis. In a view of the SVM, the basic idea is to map the input vector to a high-dimensional feature space by nonlinear mappings. In the high-dimensional feature space, a decision function is defined to construct an optimal separation hyperplane. As shown in Fig. 13, the SVM is used to analyze and evaluate the monitored data. After calculation, the value of the RMSE is 0.2110. The comparison clearly shows that the method proposed in this paper is effective and relatively accurate. Table 2 shows the comparison results of each method.

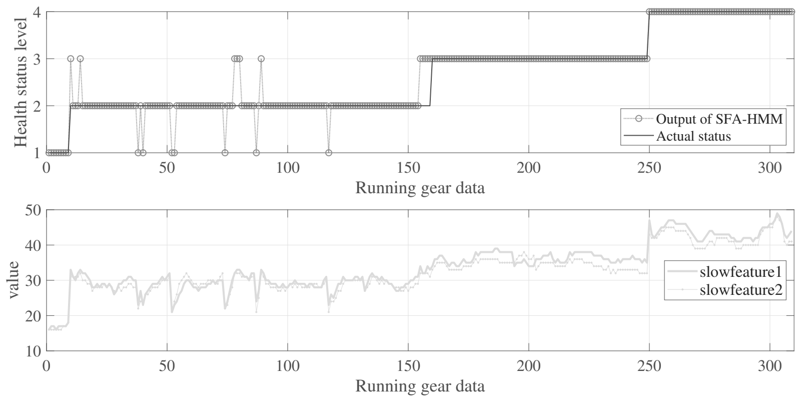


Fig. 10. Feature data and simulation results of health assessment.

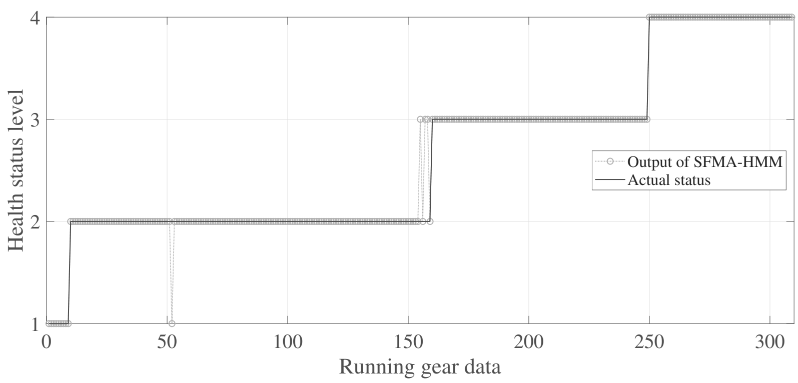


Fig. 11. SFMA simulation results.

5. Conclusions

In this research, a performance evaluation method based on the combination of SFMEA and a hidden Markov probability distribution was proposed. In the context of performance evaluation of the running gear system in high-speed trains, the following tasks were carried out. First, by analyzing the working principle, we selected the feature points and screens out the slowest features after dimensionality reduction. Then the feature selection was completed to perform feature reverse matching by correlation fitting. In the training part, the data were classified in advance based on historical information and experience. Next, the HMM completed model training and state evaluation by SFMEA; further optimization was achieved based on the analysis of monitoring statistics. Finally, the simulation results were compared to verify the effectiveness of the method.

This study made an in-depth analysis based on effective deviations exhibited in statistics. Further verification of the state transition showed that the deviation performance of the slow feature had a strong impact on the performance evaluation. It provides a possibility for a subsequent study of the correlation calculation between the deviation performance of slow characteristics and state changes. However, there is still room for improvements regarding the accuracy of the evaluation and dealing with uncertain factors, and the model needs to be further refined.

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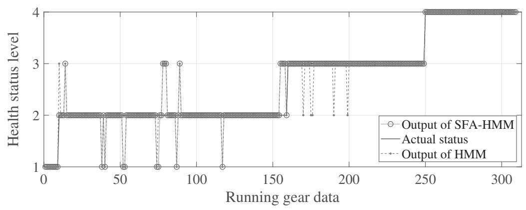

Fig. 12. Simulation results of comparison with HMM model.

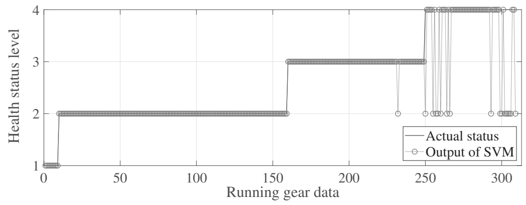

Fig. 13. SVM evaluation simulation results.

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