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LEVITATION SYSTEM CONDITION EVALUATION METHOD BASED ON WEIGHTED HELLINGER DISTANCE

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Abstract. It is important to improve the accuracy of the levitation system operation assessment, effectively guide the maintenance work of maglev trains, guarantee the safe and stable operation of the maglev system, and avoid the waste of resources. This paper proposes a levitation system condition evaluation method based on weighted Hellinger distance, which can accurately assess the levitation system state. And the feasibility and effectiveness of the algorithm are verified by using levitation system degradation simulation data.

***Key words**:* Maglev train, levitation system, weighted Hellinger distance, condition evaluation.

1. INTRODUCTION

The levitation system condition assessment, i.e., the implementation of online monitoring through the historical information and operation condition data of the levitation system, integrates these data and information to judge the operation condition of maglev trains and arrange suitable overhaul work. Therefore, how to improve the accuracy of the levitation system operation assessment, effectively guide the maglev train maintenance work, ensure the safe and stable operation of the maglev system, and avoid the waste of resources is a pressing problem.

Chen et al. proposed a multiple belief rule base (MBRB) for the health assessment of large complex electromechanical systems [1], reducing the impact of uncertainty on system assessment from the expert reliability discount model. In combination with sensor data, degradation status and health indicator prediction, [2, 3] uses information selection and information fusion methods for multi-sensor information to monitor and predict the status of industrial systems, and [4] uses Bayesian methods for parameter estimation and degradation analysis. The method based on deep learning can automatically extract the "rules" between input and output samples through learning and training, and memorize the "rules" in the form of weights to achieve state evaluation and prediction. For example, long short term memory (LSTM) has recently been widely used in system state assessment and life prediction [5]. In the evaluation of the blade degradation model of the saw blade, Li et al. used the model based on depth convolution neural network to replace the physical model [6], which greatly reduced the cost.

Amgen et al. used the improved time series algorithm to fill in the missing data [7], which solved the problem of incomplete test data. Chen Junxun et al. proposed a complex system health state assessment method based on EMD-SVD and Matian system [8] and successfully applied it to the bearing health state assessment. To solve the problem of a single data source based on vibration signal analysis method, Shan Zenghai et al. proposed a health status assessment method for hydraulic pump based on multi-sensor information fusion and multi granularity cascade forest model [9].

After feature extraction and processing of bearing signals, Yin Aijun and others combined discrete Frechet distance to make a state evaluation curve [10], which can find early equipment failures earlier and assess bearing health status. Dong Shaojiang et al. obtained low dimensional features by feature extraction and dimensionality reduction, and constructed Euclidean distance in the low dimensional feature space as the bearing performance degradation index [11], using this index to achieve bearing data labeling and establish a life state recognition model. After Chen Haitao and others established the state assessment model, they converted the assessment problem into a classification problem by calculating the distance between the point and the hyperplane [12], making the assessment result more in line with the actual situation. For research on clustering algorithms, references [13] and [14] can be consulted.

Mingtao et al. designed a transformer condition assessment method based on the DGA framework [15], which predicted the period of equipment potential fault to apparent fault by comparing the similarity between the time series to be tested and the historical fault series. Yin Aijun and others put forward Wigner Ville time-frequency distribution similarity evaluation index based on complex wavelet transform to achieve a quantitative evaluation of time-frequency distribution similarity [16], which is applied to early bearing state evaluation. Zhang Yan et al. proposed a life prediction method based on similarity of degradation features for life prediction of aero-engine simulation data [17].

In comparison to our previous work [18, 19], a condition evaluation study on aerospace engines is conducted using weighted Hellinger distance. The dataset for aerospace engines was relatively small while having a larger number of sensors, eliminating the need for feature extraction or similar operations. However, in the case of the levitation system, there is a larger volume of operational data available, but with a relatively smaller number of sensors such as gap, acceleration, current, and voltage. Therefore, it is necessary to perform feature extraction to expand the sensor state data and provide a more comprehensive reflection of the system's condition. In the levitation system condition assessment, the problem of the data degradation trend is not obvious due to multiple operating conditions of the levitation system that needs to be solved. Due to the different operating conditions, the multidimensional variable data of the levitation system will change with the different operating conditions. And the greater the difference in operating conditions, the greater the difference of variables, which leads to the change in the degradation trend of variables and makes the degradation law of the system not obvious.

To address the above problems, this paper investigates a levitation system state assessment method based on the weighted Hellinger distance, which improves the reliability of the obtained health indicators. The main contributions are as follows:

(1) Addressing the issue of low-dimensional levitation state data, statistical feature extraction is performed on the original state data to obtain a higher-dimensional feature vector that comprehensively reflects the levitation system's condition.

(2) To eliminate the influence of dimensions and different operating conditions on the state features, a classification-based standardization process is applied to the feature data.

(3) By filtering based on monotonicity, feature sequences with significant degradation trends are selected. Additionally, a health index is constructed using weighted Hellinger distance to holistically represent the health condition of the levitation system. Furthermore, degradation simulation experiments are conducted to validate the feasibility and effectiveness of the proposed method.

2. CONDITION EVALUATION METHOD BASED ON WEIGHTED HELLINGER DISTANCE

During the operation of the levitation system, the measurements from the same sensor exhibit significant variations under different operating conditions, and the dimensionality of the raw sensor data is relatively low. Therefore, before performing condition evaluation, feature extraction and pre-processing are required. In this section, statistical features of the data are extracted, and a standardized processing based on the classification of operating conditions is performed to eliminate the effects of dimensionality and different operating conditions. Based on this, feature sequences with evident degradation trends are selected based on their monotonicity as criteria for constructing health indicators.

2.1. Feature extraction and pre-processing

In the process of state evaluation for the levitation system, due to its long service life spanning several decades, the real-time degradation level in the short term is minimal and difficult to assess. Therefore, state evaluation is typically conducted at regular time intervals. For example, weekly data can be used for a weekly evaluation, or monthly data can be used for a monthly evaluation. In this paper, this time interval is referred to as the evaluation period. Within an evaluation period, it is crucial to extract features from the massive amount of sensor data that reflect the system's state during that evaluation period, considering that the levitation system is a long-duration, continuous operation system that generates a large volume of sensor data. Additionally, the types of sensor data available for the levitation system are relatively limited, including only gap, acceleration, and current sensor data, which may not fully capture the system's state during an evaluation period. Hence, a feature extraction method based on statistical measures is employed to compute various statistical features using the raw sensor data.

Assuming that in the i^{th} evaluation period, a subset of uniformly distributed operating condition data, as well as raw sensor data of gap, acceleration, and current sensors denoted as dataset $\boldsymbol{D}_i$, have been obtained through appropriate interval selection within the evaluation period:

$$\boldsymbol{D}_i = \begin{bmatrix} O_{i,t_1}^1 & \cdots & O_{i,t_1}^m & S_{i,t_1}^1 & \cdots & S_{i,t_1}^l \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ O_{i,t_j}^1 & \cdots & O_{i,t_j}^m & S_{i,t_j}^1 & \cdots & S_{i,t_j}^l \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ O_{i,t_n}^1 & \cdots & O_{i,t_n}^m & S_{i,t_n}^1 & \cdots & S_{i,t_n}^l \end{bmatrix}_{n\times(m+l)} \tag{1}$$

where, $t_1,\ldots,t_n$ represent the time points during an evaluation period when data is selected at uniform intervals, and the number of points for each evaluation period remains the same. $O_{i,t_j}^1,\ldots,O_{i,t_j}^m$ represent the different operational conditions of the levitation system at time t_j during the i^{th} evaluation period. $S_{i,t_j}^1,\ldots,S_{i,t_j}^l$ represent the corresponding raw sensor data of the levitation system at time t_j during the i^{th} evaluation period.

After obtaining dataset $\boldsymbol{D}_i$, the statistical features can be computed from this data. As a result, the feature vector $\tilde{\boldsymbol{d}}_i$ corresponding to the i^{th} evaluation period is obtained:

$$\tilde{\boldsymbol{d}}_i = \begin{bmatrix} \underset{O_{i,t_1}^1,\ldots,O_{i,t_n}^1}{\tilde{O}_i^1} & \cdots & \underset{O_{i,t_1}^m,\ldots,O_{i,t_n}^m}{\tilde{O}_i^m} & \underbrace{\tilde{S}_i^{1,1} \;\cdots\; \tilde{S}_i^{1,k}}_{S_{i,t_1}^1,\ldots,S_{i,t_n}^1} & \cdots & \underbrace{\tilde{S}_i^{l,1} \;\cdots\; \tilde{S}_i^{l,k}}_{S_{i,t_1}^l,\ldots,S_{i,t_n}^l} \end{bmatrix}_{1\times(m+kl)} \tag{2}$$

where, $\tilde{O}_i^1,\ldots,\tilde{O}_i^m$ represent statistical features calculated using the operating condition data in $\boldsymbol{D}_i$, typically selecting mean feature to reflect the main operating conditions of the system within that evaluation period; $\tilde{S}_i^{1,1},\ldots,\tilde{S}_i^{1,k}$ represent various statistical features, such as mean, minimum, maximum, and standard deviation, calculated using the raw sensor data $S_{i,t_1}^1,\ldots,S_{i,t_n}^1$. Therefore, for the i^{th} evaluation period, the condition can be represented by m operating condition features and $k\times l$ state features.

For N evaluation periods, it is possible to construct the feature set $\boldsymbol{C}$ as shown below:

$$\boldsymbol{C} = \begin{bmatrix} \tilde{\boldsymbol{d}}_1 \\ \vdots \\ \tilde{\boldsymbol{d}}_i \\ \vdots \\ \tilde{\boldsymbol{d}}_N \end{bmatrix} = \begin{bmatrix} \tilde{O}_1^1 & \cdots & \tilde{O}_1^m & \tilde{S}_1^{1,1} & \cdots & \tilde{S}_1^{1,k} & \cdots & \tilde{S}_1^{l,1} & \cdots & \tilde{S}_1^{l,k} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{O}_i^1 & \cdots & \tilde{O}_i^m & \tilde{S}_i^{1,1} & \cdots & \tilde{S}_i^{1,k} & \cdots & \tilde{S}_i^{l,1} & \cdots & \tilde{S}_i^{l,k} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{O}_N^1 & \cdots & \tilde{O}_N^m & \tilde{S}_N^{1,1} & \cdots & \tilde{S}_N^{1,k} & \cdots & \tilde{S}_N^{l,1} & \cdots & \tilde{S}_N^{l,k} \end{bmatrix}_{N\times(m+kl)} \tag{3}$$

In order to facilitate further explanation, let the equation (3) be expressed as follows:

$$\boldsymbol{C}=\begin{bmatrix}\boldsymbol{c}_1\\ \vdots\\ \boldsymbol{c}_i\\ \vdots\\ \boldsymbol{c}_N\end{bmatrix}=\begin{bmatrix}\tilde{O}_1^1 & \cdots & \tilde{O}_1^m & C_1^1 & \cdots & C_1^{kl}\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ \tilde{O}_i^1 & \cdots & \tilde{O}_i^m & C_i^1 & \cdots & C_i^{kl}\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ \tilde{O}_N^1 & \cdots & \tilde{O}_N^m & C_N^1 & \cdots & C_N^{kl}\end{bmatrix}_{N\times(m+kl)} \tag{4}$$

where, $C_1^1,\ldots,C_1^{kl}$ correspond to $\tilde{S}_1^{1,1},\ldots,\tilde{S}_1^{1,k},\ldots,\tilde{S}_1^{l,1},\ldots,\tilde{S}_1^{l,k}$ in equation (3) respectively. It can be observed that after the statistical feature extraction, the condition of the levitation system in each evaluation period can be fully characterized by the operational and status features.

Since each state feature data in equation (4) is derived from calculating statistical quantities based on raw sensor data, they have different units. Therefore, it is necessary to perform standardization before using them for state evaluation. Additionally, during the operation of the levitation system, the data obtained by sensors at each moment is always influenced by the operating conditions. Hence, a feature standardization method based on the classification of operating conditions is adopted. This method clusters all operational features into several standard operating conditions and then standardizes the corresponding state features for each standard operating condition. This approach helps reduce the impact of different operating conditions on the state features.

Assuming that there are K standard operating conditions $co_1,\ldots,co_K$, equation (4) can be reformulated:

$$\boldsymbol{C}=\begin{bmatrix} co_1\begin{cases}\boldsymbol{c}_{co_1,1}\\ \vdots\\ \boldsymbol{c}_{co_1,n_1}\end{cases}\\ \vdots\\ co_K\begin{cases}\boldsymbol{c}_{co_K,1}\\ \vdots\\ \boldsymbol{c}_{co_K,n_K}\end{cases}\end{bmatrix}=\begin{bmatrix}\boldsymbol{c}_1 & C_{co}^1\\ \vdots & \vdots\\ \boldsymbol{c}_i & C_{co}^i\\ \vdots & \vdots\\ \boldsymbol{c}_N & C_{co}^N\end{bmatrix}=\begin{bmatrix}\tilde{O}_1^1 & \cdots & \tilde{O}_1^m & C_1^1 & \cdots & C_1^{kl} & C_{co}^1\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ \tilde{O}_i^1 & \cdots & \tilde{O}_i^m & C_i^1 & \cdots & C_i^{kl} & C_{co}^i\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ \tilde{O}_N^1 & \cdots & \tilde{O}_N^m & C_N^1 & \cdots & C_N^{kl} & C_{co}^N\end{bmatrix} \tag{5}$$

where, $\boldsymbol{c}_{co_1,1},\ldots,\boldsymbol{c}_{co_1,n_1}$ represent feature vectors from $\boldsymbol{c}_1,\ldots,\boldsymbol{c}_N$, respectively, which are assigned to the standard operating condition co_1, $N=\sum_{j=1}^{K}n_j$; C_{co}^i represents the category of the standard operating condition to which C_i belongs, $C_{co}^i\in\left\{co_1,\ldots,co_K\right\}$.

The standardized processing based on the classification of operating conditions can be described:

$$\hat{s}_{i,j}=\frac{s_{i,j}-\mu_{i,j}}{\sigma_{i,j}} \tag{6}$$

where, $s_{i,j}$ represents the j^{th} state feature in the i^{th} standard operating condition, $\mu_{i,j}$ and $\sigma_{i,j}$ represent the mean and standard deviation of $s_{i,j}$, respectively; $\hat{s}_{i,j}$ represents the normalized value.

By using equation (6) to standardize the features in equation (5), the influence of operating conditions can be eliminated. Therefore, a set of standardized features $\widehat{\boldsymbol{C}}$, excluding the operating condition characteristics, can be obtained:

$$\widehat{\boldsymbol{C}}=\begin{bmatrix}\widehat{\boldsymbol{c}}_1\\ \vdots\\ \widehat{\boldsymbol{c}}_i\\ \vdots\\ \widehat{\boldsymbol{c}}_N\end{bmatrix}=\begin{bmatrix}\widehat{C}_1^1 & \cdots & \widehat{C}_1^{kl}\\ \vdots & \vdots & \vdots\\ \widehat{C}_i^1 & \cdots & \widehat{C}_i^{kl}\\ \vdots & \vdots & \vdots\\ \widehat{C}_N^1 & \cdots & \widehat{C}_N^{kl}\end{bmatrix}=\begin{bmatrix}\widehat{\boldsymbol{c}}^1 & \cdots & \widehat{\boldsymbol{c}}^{kl}\end{bmatrix}_{N\times kl} \tag{7}$$

where, $\hat{\boldsymbol{c}}_1,\ldots,\hat{\boldsymbol{c}}_N$ represent the standardized state feature vectors corresponding to each evaluation period, $\hat{\boldsymbol{c}}^1,\ldots,\hat{\boldsymbol{c}}^{kl}$ represent the feature sequences corresponding to each standardized state feature.

Furthermore, in the obtained feature set $\hat{\boldsymbol{C}}$, not every feature sequence exhibits a clear degradation trend. Therefore, to perform state evaluation more efficiently and reduce computational complexity, it is necessary to further filter out feature sequences with indistinct degradation trends. A commonly used method is to manually select feature sequences with obvious degradation trends by directly observing their changes. However, this method is subjective to some extent. To address this issue, the monotonicity of each feature sequence can be calculated, and feature sequences can be selected based on their monotonicity. The formula for calculating the monotonicity of each feature sequence in a feature set $\hat{\boldsymbol{C}}$ is as follows:

$$\mathrm{Tre}_j = \left| \sum_{i=1}^{N-1} \frac{\mathrm{sgn}\left(\hat{C}_{i+1}^j - \hat{C}_i^j\right)}{N-1} \right|, \quad \left(0 < \mathrm{Tre}_j < 1,\ j = 1,2,\ldots,kl\right) \tag{8}$$

where, Tre_j represents the monotonicity of the j^{th} feature sequence, and $\mathrm{sgn}(\cdot)$ represents the sign function. If there are multiple feature sets $\hat{\boldsymbol{C}}$, the monotonicity of the j^{th} feature sequence is obtained by taking the average.

By applying equation (8) to calculate the monotonicity of all feature sequences, the feature sequences with higher monotonicity are selected to obtain the filtered feature set $\hat{\boldsymbol{C}}^*$:

$$\hat{\boldsymbol{C}}^* = \begin{bmatrix} \hat{\boldsymbol{c}}_1^* \\ \vdots \\ \hat{\boldsymbol{c}}_i^* \\ \vdots \\ \hat{\boldsymbol{c}}_N^* \end{bmatrix} = \begin{bmatrix} \hat{C}_1^{1*} & \cdots & \hat{C}_1^{M*} \\ \vdots & \vdots & \vdots \\ \hat{C}_i^{1*} & \cdots & \hat{C}_i^{M*} \\ \vdots & \vdots & \vdots \\ \hat{C}_N^{1*} & \cdots & \hat{C}_N^{M*} \end{bmatrix} = \begin{bmatrix} \hat{\boldsymbol{c}}^{1*} & \cdots & \hat{\boldsymbol{c}}^{M*} \end{bmatrix}_{N\times M} \tag{9}$$

where, $\hat{\boldsymbol{c}}_1^*,\ldots,\hat{\boldsymbol{c}}_N^*$ represent the feature vectors corresponding to each evaluation period after filtering, $\hat{\boldsymbol{c}}^{1*},\ldots,\hat{\boldsymbol{c}}^{M*}$ represent the filtered feature sequences, $\left\{\hat{\boldsymbol{c}}^{1*},\ldots,\hat{\boldsymbol{c}}^{M*}\right\} \subset \left\{\hat{\boldsymbol{c}}^1,\ldots,\hat{\boldsymbol{c}}^{kl}\right\} (M \le kl)$.

At this point, the filtered feature sequences will exhibit a clear monotonic trend, which can effectively reflect the degradation trend of the system. These sequences can be utilized in subsequent state evaluation methods.

2.2. Condition evaluation method based on Hellinger distance

After obtaining the feature sequences with clear degradation trends through the aforementioned feature extraction and preprocessing, it is necessary to construct a health indicator using these sequences to comprehensively reflect the degradation state of the system. In this section, the weighted Hellinger distance is used to build the health indicator.

In probability and statistics, the Hellinger distance is used to measure the similarity between two probability distributions. Assuming there are two probability distributions, $P = \{p_i\}_{i\in[n]}$ and $Q = \{q_i\}_{i\in[n]}$, the Hellinger distance between them is defined as follows:

$$h(P,Q) = \frac{1}{\sqrt{2}} \cdot \left\| \sqrt{P} - \sqrt{Q} \right\|_2 \tag{10}$$

For the filtered feature sequences $\hat{\boldsymbol{c}}^{j*} = \begin{bmatrix} \hat{C}_1^{j*} & \cdots & \hat{C}_N^{j*} \end{bmatrix}^{\mathrm{T}}$, starting from the first evaluation period, a segment of N_{ref} sequences is selected as the reference sequence. This reference sequence is denoted as:

$$\widehat{\boldsymbol{c}}_{\mathrm{ref}}^{j*} = \left[\widehat{C}_1^{j*} \quad \cdots \quad \widehat{C}_{N_{\mathrm{ref}}}^{j*} \right]^{\mathrm{T}} \tag{11}$$

To calculate the similarity between the i^{th} evaluation period and the first evaluation period, a segment of N_{ref} sequences is also selected in the i^{th} evaluation period. This segment of sequences is used to compute the Hellinger distance with the reference sequence $\widehat{\boldsymbol{c}}_{\mathrm{ref}}^{j*}$. The feature sequence $\widehat{\boldsymbol{c}}_i^{j*}$ selected for the i^{th} evaluation period can be represented as:

$$\widehat{\boldsymbol{c}}_i^{j*} = \left[\widehat{C}_{i-N_{\mathrm{ref}}+1}^{j*} \quad \cdots \quad \widehat{C}_i^{j*} \right]^{\mathrm{T}} \tag{12}$$

By using equation (10), the Hellinger distance h_i^{j*} between the reference sequence $\widehat{\boldsymbol{c}}_{\mathrm{ref}}^{j*}$ represented by equation (11) and the feature sequence $\widehat{\boldsymbol{c}}_i^{j*}$ represented by equation (12) can be calculated:

$$h_i^{j*} = \frac{1}{\sqrt{2}} \left\| \sqrt{\widehat{\boldsymbol{c}}_{\mathrm{ref}}^{j*}} - \sqrt{\widehat{\boldsymbol{c}}_i^{j*}} \right\|_2 \quad \left(i = 1,2,\ldots,N;\ j = 1,2,\ldots,M \right) \tag{13}$$

At this point, it can be assumed that the reference sequence reflects the system's state during initial normal operation, indicating that these reference sequences represent a healthy state of the system. A larger calculated Hellinger distance indicates a smaller similarity to the reference sequence, suggesting a greater degree of degradation in the system during that evaluation period. Conversely, a smaller calculated Hellinger distance indicates a higher similarity to the reference sequence, indicating a lesser degree of degradation in the system during that evaluation period.

Simultaneously, each feature represents a local analysis of the system and cannot capture the complete information about the overall degradation of the system. Therefore, it is necessary to integrate the various features corresponding to the same evaluation period to comprehensively describe the degradation of the system and obtain an accurate system health state curve. For the i^{th} evaluation period, the weighted Hellinger distance for each feature is calculated by assigning weights based on the ratio of the Hellinger distance value of each feature to the sum of the Hellinger distance values of all features. The weighted Hellinger distances for all features are then calculated, serving as the health indicator HI_i that comprehensively represents the system’s state for the i^{th} evaluation period:

$$\mathrm{HI}_i = 1 - \frac{\sum_{j=1}^{M} \left(h_i^{j*} \right)^2}{\sum_{j=1}^{M} h_i^{j*}} \tag{14}$$

In addition, to evaluate the effectiveness of the state evaluation method, the overall fitting trend R^2 and root mean square error RMSE are selected as evaluation metrics:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(\widetilde{\mathrm{HI}}_i - \mathrm{HI}_i \right)^2}{\sum_{i=1}^{N} \left(\widetilde{\mathrm{HI}}_i - \overline{\widetilde{\mathrm{HI}}} \right)^2} \tag{15}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \left(\widetilde{\mathrm{HI}}_i - \mathrm{HI}_i \right)^2}{N}} \tag{16}$$

where, $\widetilde{\mathrm{HI}}_i$ represents the true health indicator value of the system for the i^{th} evaluation period, and $\overline{\widetilde{\mathrm{HI}}}$ represents the mean value of the true health indicator values. A smaller value of RMSE indicates a better evaluation performance, while a larger value indicates a poorer evaluation performance. The closer F^2 is to 1, the more the constructed health indicator resembles the true health indicator.

Finally, the condition evaluation algorithm can be summarized as follows.

Algorithm 1: Levitation system condition evaluation based on weighted Hellinger distance

Input: original operating condition data and state data of the levitation system

Output: health index HI_i

1: Equally spaced selection, a data set $\boldsymbol{D}_i$ for each evaluation period according to equation (1) is constructed;

2: Perform statistical feature extraction on $\boldsymbol{D}_i$ according to equation (2);

3: Construct feature dataset $\boldsymbol{C}$ for all evaluation periods according to equations (3) and (4);

4: Utilize the K-means clustering algorithm to cluster the operating conditions and obtain the dataset as shown in equation (5);

5: Normalize the dataset shown in equation (5) according to equation (6) to obtain the standardized feature dataset $\widehat{\boldsymbol{C}}$ as shown in equation (7);

6: Calculate the monotonicity of feature sequences according to equation (8), filter out the feature sequences with a strong monotonic trend, and obtain the feature dataset $\widehat{\boldsymbol{C}}^*$ as shown in equation (9);

7: Calculate the health index HI_i according to equations (10)–(14);

8: **Return** HI_i .

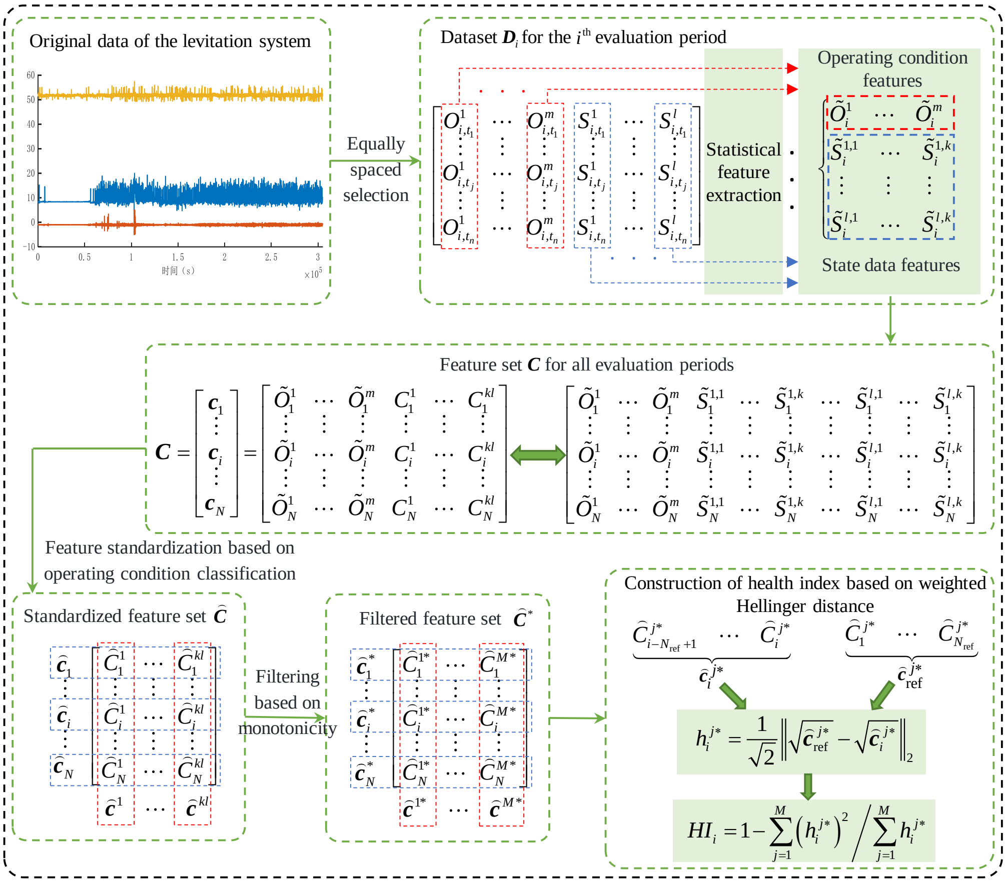

Fig. 1 – Flow chart of condition evaluation.

3. CONDITION EVALUATION PROCESS AND VERIFICATION

The condition evaluation process is illustrated in Fig. 1. First, the feature extraction is performed on the equally spaced and statistically calculated data sets obtained from the original data of the levitation system, resulting in the feature data set for all evaluation periods. Then, the operating condition features are used for classification and standardization, resulting in the standardized feature data. Subsequently, the feature data with better degradation trends is selected based on monotonicity. Finally, the weighted Hellinger distance is used to calculate the health index.

3.1. Acquisition of degradation simulation data of levitation system

Because the maglev train has been put into operation for a short time, the existing operation line data is difficult to verify the state assessment method. This chapter is based on the levitation system model of Changsha Maglev Express Line Maglev train parameters, simulates the controller degradation to generate simulation data, and verifies the effectiveness of this method through simulation data.

Table 1

Changsha Maglev Express Train Single Point Parameter Table

Changsha Maglev Express Train Single Point Parameter Table			
Parameter	***Parameter value***	***Parameter***	***Parameter value***
m	535 kg	M	665 kg
R	0.92 Ω	A	0.038 m^2
L	1.36 m	d	0.348 m
a	0.028 m	z_0	0.01 m
N	360	i_0	28.0 A
σ	5×10^6 m/s	μ_0	$4\pi\times10^{-7}$ H/m

In this section, the controller degradation is taken as the background. The HI calculated according to the following equation (17) is used as the real HI in the equations (15) and (16) to evaluate the HI calculation method based on the weighted Hellinger distance, where $a = \frac{1}{400}$ and $b = 0.006$:

$$\mathrm{HI}_t = 1 + a\left(1 - e^{b \cdot t}\right) \tag{17}$$

Finally, the maximum number of cycles to degrade the controller from 1 to 0 is 1000.

500 samples are generated through simulation experiments, and randomly divided into 400 training samples and 100 test samples by cross validation method. Each sample is the data of levitation system degradation from different degradation time (from normal to failure) to failure.

3.2. Experimental results and analysis

By clustering historical operating conditions with the K-means clustering algorithm, it is found that the clustering results of three types of operating conditions of simulation data are 30 core conditions.

The Fig. 2 and Fig. 3 show the curve of the 8$^{\text{th}}$ and 10$^{\text{th}}$ features in the 165$^{\text{th}}$ group of training samples. It can be seen that the 10$^{\text{th}}$ feature has a significant downward trend, while the 8$^{\text{th}}$ feature has no significant change. And because of the influence of different operating conditions, the characteristic curve appears obvious vibration phenomenon, which blurs the changing trend of the characteristics.

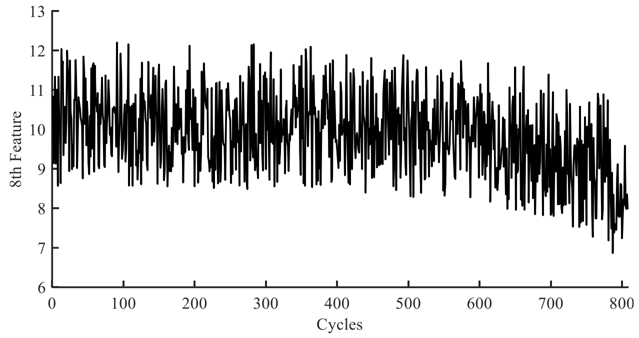

Fig. 2 – The 8th feature curve in the 165th training sample.

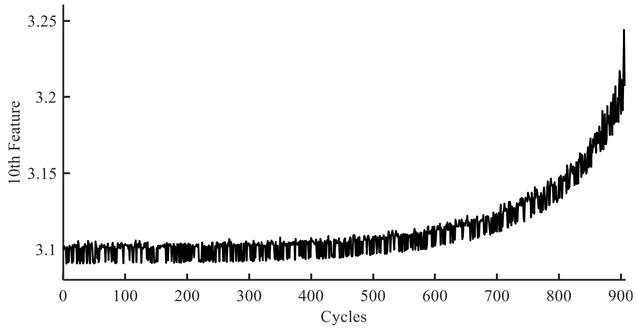

Fig. 3 – The 10th feature curve in the 165th training sample.

The feature is standardized by equation (6). Fig. 4 and Fig. 5 show the 8th and 10th feature curves after standardization respectively. Compared with Fig. 2 and Fig. 3, the feature fluctuation after standardization is significantly reduced and has an obvious change trend. It is verified that this method can effectively eliminate the influence of different core conditions on features, and also make the changing trend of features more obvious.

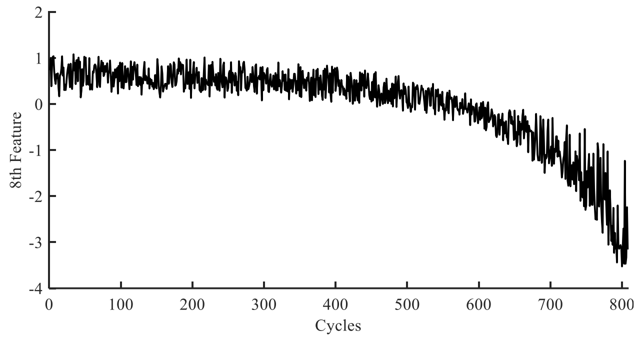

Fig. 4 – The 8th feature curve after standardization.

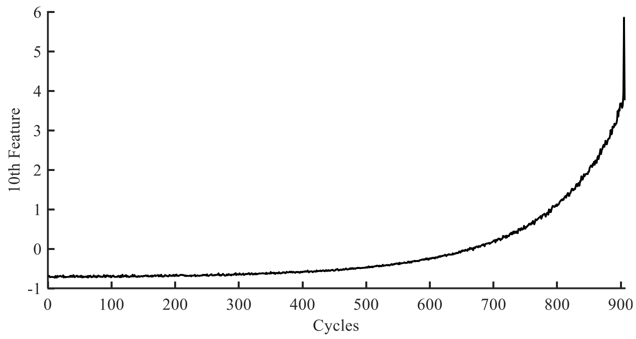

Fig. 5 – The 10th feature curve after standardization.

For the generated simulation data, take 100 groups of data randomly divided into historical data and 400 groups of data as test data, and use the weighted Hellinger distance to obtain the estimated HI curve of a test sample, as shown in the Fig. 6.

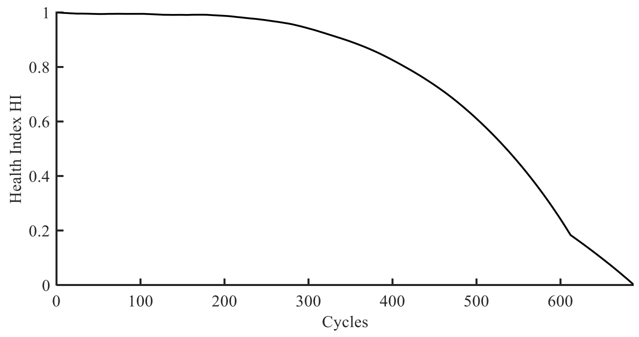

Fig. 6 – Weighted Hellinger distance curve of a test sample.

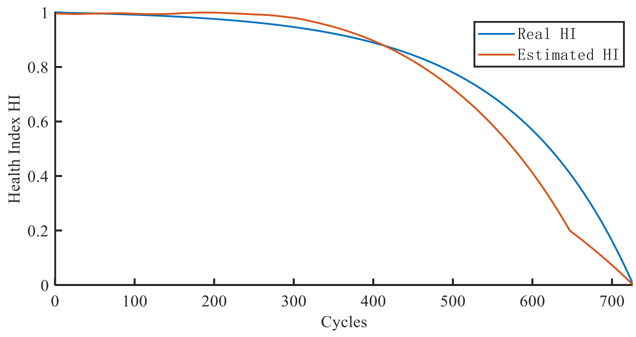

Fig. 7 – The estimated HI and the real HI in a test sample.

As shown in Fig. 6, with the increase in data degradation, the state curve of the test sample based on the weighted Hellinger distance gradually degrades to 0. As time goes on, the performance of the levitation system gradually degrades until failure occurs (Hellinger Distance = threshold). The estimated HI is calculated by the equation (14) to obtain the control system degradation curve in [0,1] interval, and the real HI and the estimated HI curve are filtered by the moving average filtering method with a window of 21 (10 HIs for the current HI and 10 HIs for the front and back). Figure 7 shows the comparison between the estimated HI and the real HI in a test sample.

It can be seen from Fig. 7 that there is a certain difference between the values of the two HIs at the same cycle number. This is because this section adds real noise to the gap, current and acceleration of the simulation model, resulting in some differences between the changing trend of the system HI and that of the controller HI under the cyclic influence of the real noise.

Figure 8 and Figure 9 show the overall fitting trend R^2 and root mean square error RMSE of 400 training samples, respectively. The maximum RMSE is 0.0772, the minimum RMSE is 0.0644, and the average RMSE is 0.0708. The maximum R^2 is 0.9382, the minimum R^2 is 0.9023, and the average value of R^2 is 0.9217. This shows that the HI obtained by the method in this chapter is close to the real HI.

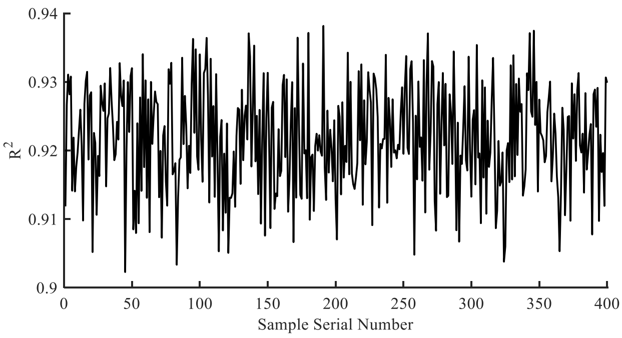

Fig. 8 – Overall fitting trend R^2 of 400 training samples.

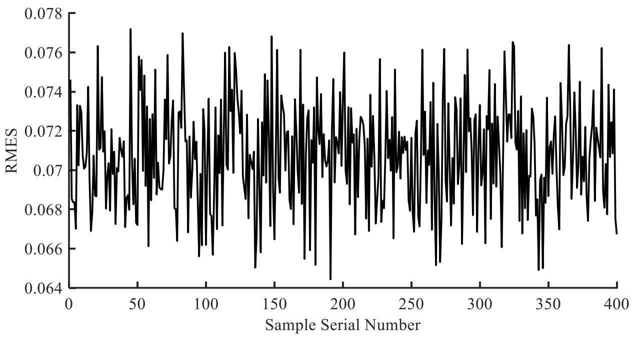

Fig. 9 – Root mean square error RMSE of 400 training samples.

4. CONCLUSION

Aiming at the problem of levitation system state evaluation, this paper proposes a state evaluation method based on weighted Hellinger distance. Firstly, K-means is used to cluster the operating conditions of the levitation system, and the cluster center of the clustering results is taken as the standard core state. In order to solve the problem that the measurement size of HI is different under different operating conditions, the feature sequence is converted to the feature sequence under the standard core state after standardization. The weighted Hellinger distance is used to obtain the estimated HI. The simulation results show that the method is effective.

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