Hindawi
Mathematical Problems in Engineering
Volume 2024, Article ID 5088057, 12 pages
https://doi.org/10.1155/2024/5088057

Research Article

A Health Status Assessment Method of Fluid Loop System Based on Hierarchical Multi-Information Fusion

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Received 5 August 2023; Revised 12 October 2023; Accepted 23 December 2023; Published 25 January 2024

Academic Editor: Gianpaolo Di Bona

As a kind of thermal control device, fluid loop systems must operate with the demands of high safety, high reliability, and long life. In order to accurately assess the health status of fluid loop systems, a hierarchical multi-information fusion (HMIF) method is proposed in this paper. Considering that fluid loop systems generally have distinct structural hierarchies, the health evaluation process in this method is divided into three levels, which are the indicator level, the component level, and the system level. In the evaluation process, the health indices are, respectively, constructed to quantify the health status at the three levels. At the indicator level, One-Class support vector machine algorithm is used to obtain the distribution space of each state monitoring indicator under a normal state. The indicator-level health indices are evaluated by calculating the ratio of the data located in the distribution space to the overall data. At the component level, a fuzzy theory is used to calculate the health indices of the component level. Health indices at the indicator level are first converted to membership degree by membership degree function. Then, the evaluation fusion strategy is used to deduce the membership degree of the component level. The health indices at the component level are obtained from the mapping relationship between the membership degree and the health index. At the system level, an adaptive weight adjustment strategy is proposed to fuze all component-level health indices. Taking a practical fluid loop system as an example, health indices at the three levels evaluated by the HMIF method are compared with the actual status. The results indicate that the proposed method can correctly judge the health state of the system and provide a reference for the maintenance and fault diagnosis of fluid loop systems.

1. Introduction

Fluid loop systems are important devices in the active thermal control field. Because of their strong heat regulation capacity and flexible thermal management, fluid loop systems are widely used in the establishment of a constant temperature environment and temperature control in industry, spacecraft, military, and other important fields [1]. Their long-term and good performance operation is crucial to the success of engineering tasks and even the safety of personnel. Therefore, to ensure the normal and stable operation of fluid loop systems has been widely concerned by scholars.

During the operation of fluid loop systems, if the fault is not detected and repaired in a timely manner, it may lead to catastrophic accidents. It is important to detect early symptoms of faults in order to avoid serious consequences. Breakdown maintenance is a type of reactive measure that cannot avoid the occurrence of faults and the significant negative effects caused by faults. Time-based maintenance cannot accurately assess the system status, which often waste manpower and material resources. In order to solve the above problems, condition-based maintenance (CBM) has been developed. It monitors and evaluates the health status of the system and adopts corresponding maintenance strategies after finding abnormalities. Therefore, in view of the operating characteristics of the fluid loop system, only the CBM is suitable for its operation and maintenance [2–5].

Health-status assessment is one of the key technologies of CBM. It is of great significance to accurately assess the health status of the system. There are two main ways to evaluate health status. One is to evaluate the health degree of the system [6]. The running state of a complex system is divided into several degrees to describe the multivalued state of the system. The health degree of the system is evaluated by analyzing the monitoring data in the process of running state. This kind of health status assessment method research is relatively mature, but there is no unified standard for health status classification. The other is to quantify the health status contained in the state data by extracting the corresponding feature. This feature is defined as a health index. In this way, the health status of the system can be quantitatively characterized [7]. If the health index of the fluid loop system can be evaluated correctly, the degradation information of system performance can be intuitively evaluated. To a certain extent, the health index can be transformed into a failure rate, which is convenient for accurate maintenance decision-making.

At present, health index evaluation methods can be divided into three kinds from different driving sources, namely, model-driven methods, knowledge-driven methods, and data-driven methods. Model-driven methods are a kind of physical model designed by relevant experts, who deeply study the principle of system degradation in the process of long-term work. Such as the Mahalanobis distance method [8, 9], fusion weight calculation method [10], Euclidean distance method [11], fuzzy theory method [12–14], and so on. However, since the model-driven methods require prior knowledge to determine the weights and model parameters as well as the idealized assumptions of the model, it is difficult to adapt to various complex factors during the operation of the system. This leads to a poor practical effect of the method. Knowledge-driven methods evaluate the health status through knowledge acquisition and knowledge representation. Due to the limitation of knowledge and experience, these methods are difficult to implement. The knowledge representation also faces the problem of knowledge normalization [15]. Data-driven methods are the most popular at present. These methods make full use of the advantages of machine learning and artificial intelligence. The application of linear regression, support vector machine (SVM) [16–18], support vector data description [19–21], neural network, and deep learning theory [22–24] has strongly promoted the development of health index evaluation research.

Fluid loop systems are composed of many different types of components, and each component has multiple monitoring objects. As a result, the same health evaluation method may have great differences in the evaluation effect for different components. Some scholars have proposed integrated methods to solve such problems. Wei et al. [25] built a deep well thermal environment evaluation model by integrating the analytic hierarchy process and fuzzy theory and evaluated 21 working faces of a gold mine. Ye et al. [26] established a safety evaluation index system for underground ventilation systems in uranium mines based on AHP and fuzzy comprehensive assessment. To help mine management assess the risk of scaring mining in extremely hot and humid environments, Shu et al. [27] proposed a multi-indicator hierarchical model. The entropy weighting method was used to determine the index weights and derive the multi-index measure evaluation matrix. Some applications have demonstrated that these integrated methods are capable of assessing the health of complex systems.

In this paper, a health assessment method of a fluid loop system based on hierarchical multi-information fusion (HMIF) is proposed. This method divides the health assessment process into three levels: indicator level, component level, and system level. First, the One-Class SVM algorithm is used to obtain the health index of indicator-level data in the fluid loop system. Then, the fuzzy theory method is applied to deal with the uncertainty between different indicators in each component to obtain the component-level health index. Finally, an adaptively variable weight strategy is designed to estimate the system-level health index by fuzing the component-level health index. The method proposed in this paper can quantitatively estimate the health state of fluid loop systems. It is beneficial to provide a reliable reference for the health maintenance of the system.

This paper is organized as follows: In Section 2, the architecture of the HMIF method is generally described. The theoretical background and algorithms of the key techniques involved in the method are discussed in detail. In Section 3, the process of evaluating the health status of a practical fluid loop system using the HMIF method is provided and analyzed. Finally, the conclusion of this work is given in Section 4.

2. Health State Assessment Method for Fluid Loop Systems

Fluid loop systems are complex coupled systems. As shown in Figure 1, they are generally composed of pump, valve, filter, compensator, and other components. Each component is connected by a large number of pipes to form a system loop. In order to collect the monitoring data of components during operation, many sensors are installed in the system. Because of the different monitored objects, the monitoring data have diverse manifestations, such as continuous dynamic curves and step switches. Moreover, with the change in the working condition of systems, the monitoring data, such as speed, pressure, and flow rate, may change in different ranges and exhibit various statistical characteristics. With the help of data processing, indicators contained in the monitoring data are extracted. Due to the diversity of monitoring data, it is difficult to formulate a unified standard to evaluate the health indices utilizing indicators. In addition, there is a complicated relationship between components and indicators. It leads to information redundancy and conflict in the health indices evaluation of components. The health status of systems is evaluated by fuzing the health indices of all components that this system contains. The health status of components has different effects on the system's performance. Therefore, it is necessary to design an appropriate assessment strategy for the health status assessment of the system.

Health indices are obtained by analyzing a variety of monitoring data during the system operation. These health indices provide meaningful information for maintaining the operation of fluid loop systems with long life and good

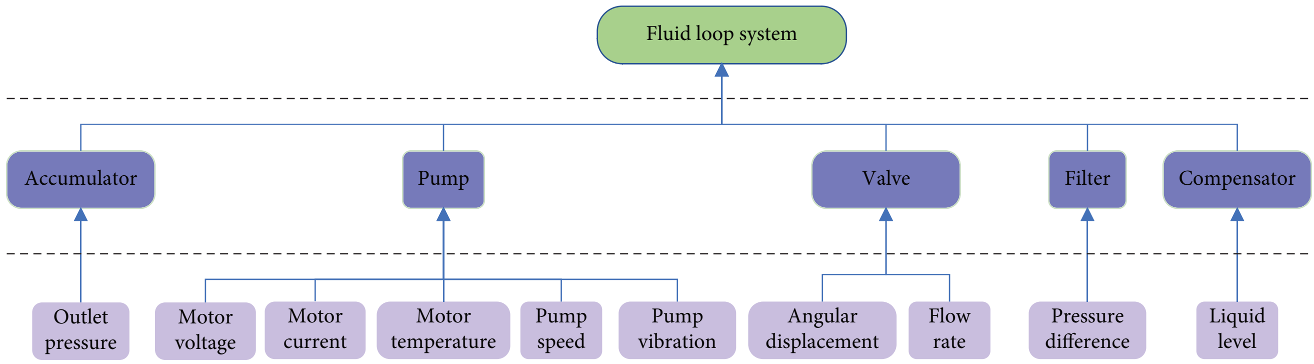


FIGURE 1: Architecture diagram of fluid loop system.

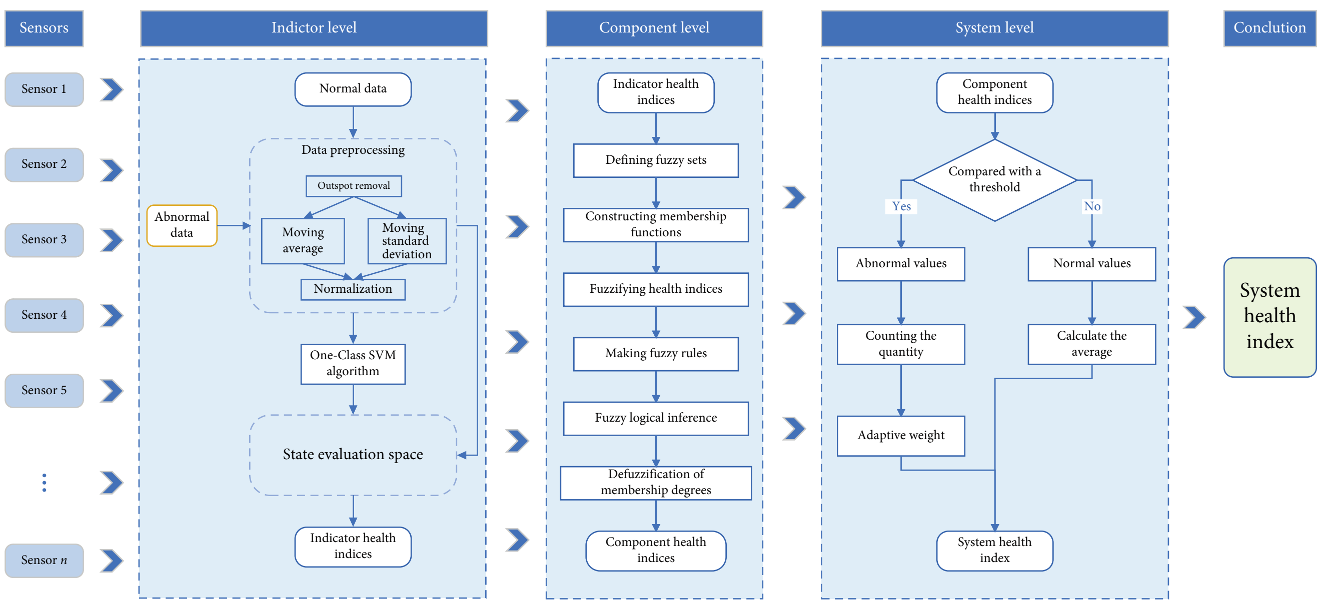


FIGURE 2: Flow diagram of hierarchical multi-information fusion method.

performance. Therefore, it is necessary to make a comprehensive evaluation for the system. The application flowchart of the hierarchical multi-information fusion method proposed in this paper is shown in Figure 2. In view of the distinct structural characteristics of the fluid loop system, the health status assessment process is divided into three levels: indicator level, component level, and system level. At the indicator level, moving average and moving standard deviation processing are used to reduce the random error interference of monitoring data and extract status indicators contained in the monitoring data. In order to solve the problem that it is difficult to establish a unified standard to judge the health status because of the differences between the indicators, this paper constructs the data distribution space model under a normal state for each indicator. The essence of the health status assessment problem is pattern recognition. As one of the important pattern recognition algorithms, One-Class SVM has the ability of inhomogeneous data separation in high-dimensional space. Therefore, this paper chooses this algorithm to build the evaluation model. The algorithm outputs binary evaluation results, and then the quantitative evaluation results of health status are obtained by counting the number of positive labels. At the component level, some traditional evaluation methods are not applicable due to the uncertainty of multiple indicators in the evaluation of the health status of a certain component. The fuzzy evaluation method, which fuzes the redundant information and compromises the conflicting information, is used to reduce the impact of uncertainty in the health status assessment of components. For the system, the health status of each component has a different influence on the performance of the system. Moreover, the changes of the health index of a single component have little impact on the system-level health status evaluation if some fixed weights are given. Therefore, an adaptive weight method is designed to integrate the health status of all components, which is used to conduct a comprehensive health evaluation of the whole system and provide decision-making support for maintenance personnel.

2.1. Health Status Assessment for Indicator Level

2.1.1. One-Class SVM. One-Class SVM based on statistical theory is a typical kernel analysis approach. Its idea is to define a maximum interval classifier in the feature space. The classifier is used to separate the data with different distributions as much as possible. One-Class SVM transforms the interval maximization problem into a convex quadratic programing problem and solves it by an optimal method. Suppose that there are samples $x_i (1 \le i \le l)$ from the same distribution, where l is the number of samples. The sample data are mapped to high-dimensional feature space F by nonlinear mapping φ. Then, a compact spatial region D containing as much sample data as possible is found in F and separated from the heterogeneous data at the largest interval. ω is set to determine the size of the compact space D. The optimization problem can be expressed by the quadratic program, as shown in Equation (1).

$$\begin{aligned} &\min_{\omega\in F, \xi_i\in\mathbb{R}^n, \rho\in\mathbb{R}} : \frac{1}{2}\|\omega\|^2 + \frac{1}{\nu l}\sum_{i=1}^{l}\xi_i - \rho \\ &\text{subject to } \langle \omega, \varphi(x_i)\rangle \ge \rho - \xi_i, \xi_i \ge 0, \end{aligned} \tag{1}$$

where ξ_i is the slack variable, which allows some samples to be on the side that violates the constraint; ρ is the boundary threshold; ν is tradeoff parameter, which determines the volume of the region and the tradeoff of the number of samples that the region contains, and its value ranges from 0 to 1. If ω and ρ can be found, the decision function $f(x) = \mathrm{sgn}(\langle \omega, \varphi(x)\rangle - \rho)$ will be positive for most samples.

The Lagrange function is constructed to solve the optimization problem.

$$\begin{aligned} L(\omega, \xi, \rho, \alpha, \gamma) = \frac{1}{2}\|\omega\|^2 + \frac{1}{\nu l}\sum_{i=1}^{l}\xi_i - \rho - \sum_{i=1}^{l}\alpha_i(\langle \omega, \varphi(x_i)\rangle \\ - \rho + \xi_i) - \sum_{i=1}^{l}\varsigma_i\xi_i, \alpha_i \ge 0, \varsigma_i \ge 0, \end{aligned} \tag{2}$$

where α_i and ς_i is the Lagrange coefficient.

By taking the partial derivation of Equation (2) to ω, ξ_i, and ρ, and making the partial derivative equal to 0, the Equations (3) and (4) can be obtained.

$$\omega = \sum_{i=1}^{l}\alpha_i\varphi(x_i), \tag{3}$$

$$0 \le \alpha_i \le \frac{1}{\nu l}, \sum_{i=1}^{l}\alpha_i = 1. \tag{4}$$

Equations (3) and (4) are introduced into Equation (1), and the kernel function $K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j)\rangle$ is introduced at the same time. As a result, Equation (5) is obtained.

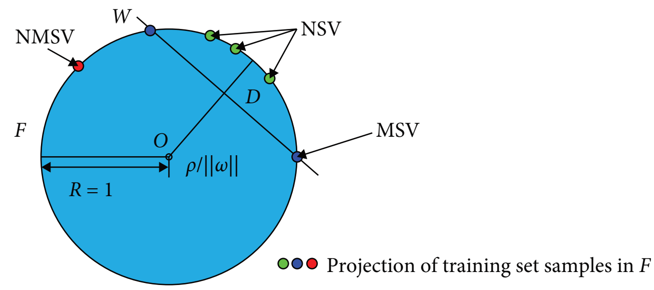


Figure 3: The geometric description of One-Class support vector machines.

$$\begin{aligned} &\min_{\alpha} : \frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j K(x_i, x_j) \\ &\text{subject to } 0 \le \alpha_i \le \frac{1}{\nu l}, \sum_{i=1}^{l}\alpha_i = 1. \end{aligned} \tag{5}$$

Equation (5) is a quadratic programing problem, which can be solved by standard QP routines. The sample x_i corresponding to $\alpha_i > 0$ is called support vector, and the dataset composed of support vectors is denoted as SV. The distribution of all target samples in feature space completely depends on this dataset. The decision function is defined as follows:

$$f(x) = \sum_{x_i\in SV}\alpha_i K(x_i, x) - \rho, \tag{6}$$

when $f(x) > 0$, x is determined to come from the source distribution, i.e., belongs to the distribution region D determined by the target sample. When $f(x) < 0$, x is determined not to belong to the source distribution and is located outside the distribution region D. According to the positive and negative results of the decision function, it is judged whether the new samples belong to the distribution of target samples.

The decision function $f(x) > 0$ of the nonsupport vector set, which lies in the distribution region D, is denoted as NSV. The support vector set of $f(x) = 0$ is called the margin support vector set and is denoted as MSV. The support vector set of $f(x) < 0$ is called the nonmargin support vector set and is denoted as NMSV. The parameter ν is the upper bound of the nonmargin support vector and the lower bound of the margin support vector. When training the same sample set X, adjusting this parameter can change the samples contained in NSV, MSV, and NMSV. The smaller ν, the more samples contained in NSV, and the fewer samples contained in NMSV.

2.1.2. Indicator-Level Health Status Assessment Process. For indicator-level health status evaluation, the distribution space is constructed by the indicators in a normal state. Therefore, the state evaluation process is simplified as the problem of judging anomalies in a normal state without obtaining abnormal samples in advance. One-Class SVM is an effective way to solve this problem. In Figure 3, the two types of data samples are represented by the green dot and

Table 1: Set of comments for component health condition assessment.

Degree	State	Status description
h_1	Healthy	The operating condition of the components is normal
h_2	Degradation	The health state of component is degraded
h_3	Severe degradation	The component has potential accidents
h_4	Hazard	The component has been damaged
h_5	Severe hazard	The component has been damaged to stop working

the red dot, W is a classification line; additionally, $\rho/||\omega||$ is the furthest distance from W. The optimal distribution region D is the part separated by W away from the center of the hypersphere. According to the foregoing information, it can be concluded that W is the optimal classification hyperplane.

The procedures of health status classification are as follows:

(1) Data preprocessing. The moving average feature sequence and moving standard deviation (moving STD) feature sequence of the input sample data are calculated. Then, the two sets of sequences are normalized. The effect of moving average and moving STD is to smooth data fluctuations and thus reflect the overall trend of the data. Normalization processing can effectively prevent the characteristics of large value regions from suppressing the characteristics of small value regions and can also reduce the computational complexity and improve the computational accuracy.

(2) Finding the maximum interval classifier. Moving averages and moving standard deviation sequences are used as training sets. One-Class SVM algorithm is used to find the maximum interval classifier in feature space, which is established by training data.

(3) Health assessment. The moving average and the moving STD sequence of the data to be evaluated are calculated and normalized utilizing the same parameters as those used in the training data normalization. These sequences are fed into the maximum interval classifier and wait to be evaluated.

(4) Calculating the health index. The number of points of sequences is counted which is located in the optimal distribution space. The ratio of these points to the total sequence length is considered the health index.

With the above procedures, the quantitative description of indicator-level health status is realized.

2.2. Health Status Assessment for Component Level. Fuzzy evaluation availably deals with various fuzzy and uncertain information and makes the evaluation results more stable and reliable. In the component-level health status assessment process, information redundancy and information conflict are unavoidable. The fuzzy evaluation is used to reduce the information redundancy and eliminate the information conflict, which is produced at the indicator-level health status assessment, and to provide the component-level health status assessment.

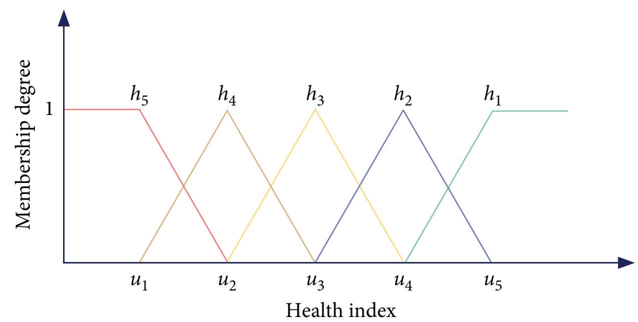


Figure 4: Distribution of triangular membership function.

2.2.1. Defining Fuzzy Sets. To represent the health state at the component level, five degrees are defined as the assessment fuzzy sets. They are healthy, degradation, severe degradation, hazard, and severe hazard, respectively. Denote the fuzzy sets as $H = \{h_1, h_2, h_3, h_4, h_5\}$. The description of component health status and evaluation results of the corresponding degrees is shown in Table 1.

2.2.2. Constructing Membership Functions and Fuzzifying Health Indices. There are many types of membership functions, such as triangular, trapezoidal, and normal. Because of the advantage of easy algebraic operation of the triangular membership function, it is used for fuzzy evaluation. The distribution of triangular membership functions is shown in Figure 4.

The membership functions of health indices corresponding to different health degrees in a fuzzy set are shown in Table 2. The domain $\{u_1, u_2, u_3, u_4, u_5\}$ in the membership function is generally determined based on expert experience.

According to the selected membership functions, the membership degrees of indicator-level health indices to each health degree can be calculated. That is, the indicator-level health indices are fuzzified. After that, the membership degrees are constructed into a fuzzy evaluation matrix.

2.2.3. Making Fuzzy Rules. Fuzzy rules are established based on past expert experience. For example, the health degrees of two indicators are h_3 and h_4 in the past experience. The health degree of the component corresponding to these two indicators is h_4. Then, the fuzzy rule $\text{Rule1}(h_3, h_4; h_4)$ is obtained based on the above experience. Such experience can build a fuzzy rule base, as shown in Figure 5. If expert

Table 2: Membership functions corresponding to different levels.

Degree	Membership function	Degree	Membership function
h_1	$A_{h_1}(x) = \begin{cases} 0,\ x \in (0,\ u_4) \\ \dfrac{x - u_4}{u_5 - u_4},\ x \in [u_4,\ u_5) \\ 1,\ x \in [u_5,\ +\infty) \end{cases}$	h_2	$A_{h_2}(x) = \begin{cases} 0,\ x \in (0,\ u_3)\&[u_5,\ +\infty) \\ \dfrac{x - u_3}{u_4 - u_3},\ x \in [u_3,\ u_4) \\ 1 - \dfrac{x - u_4}{u_5 - u_4},\ x \in [u_4,\ u_5) \end{cases}$
h_3	$A_{h_3}(x) = \begin{cases} 0,\ x \in (0,\ u_2)\&[u_4,\ +\infty) \\ \dfrac{x - u_2}{u_3 - u_2},\ x \in [u_2,\ u_3) \\ 1 - \dfrac{x - u_3}{u_4 - u_3},\ x \in [u_3,\ u_4) \end{cases}$	h_4	$A_{h_4}(x) = \begin{cases} 0,\ x \in (0,\ u_1)\&[u_3,\ +\infty) \\ \dfrac{x - u_1}{u_2 - u_1},\ x \in [u_1,\ u_2) \\ 1 - \dfrac{x - u_2}{u_3 - u_2},\ x \in [u_2,\ u_3) \end{cases}$
h_5	$A_{h_5}(x) = \begin{cases} 1,\ x \in (0,\ u_1) \\ 1 - \dfrac{x - u_1}{u_2 - u_1},\ x \in [u_1,\ u_2) \\ 0,\ x \in [u_2,\ +\infty) \end{cases}$	—	—

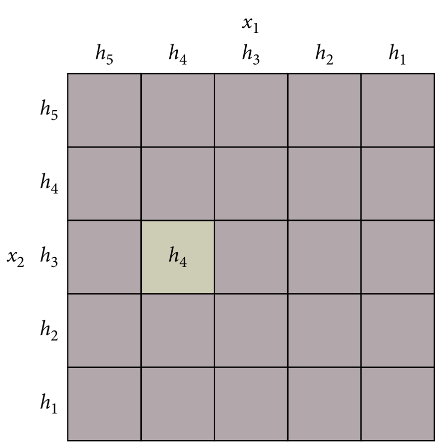


Figure 5: Schematic representation of the fuzzy rule base.

experience is made available effectively, the obtained rules can fill the whole fuzzy rule base.

2.2.4. Fuzzy Logical Inference. To implement fuzzy logical inference, the relation generation process, and the inference synthesis process need to be done. In the component-level health assessment process, membership degrees of health indices at the indicator-level are taken as the inputs of fuzzy logical inference. The outputs of fuzzy logical inference are the membership degrees of component health states. The processing of making fuzzy rules is to establish the relationship between inputs and outputs. The inference synthesis process is to use some approaches to reasonably infer the fuzzy output of the new input by using the previously defined fuzzy rules. After the relation generation process and inference synthesis process are determined, fuzzy logical inference can be carried out.

The Mamdani inference synthesis algorithm [28] is widespread acceptance and has the advantage of intuitiveness, suitability for human input, and ease of interpretability. To achieve the inference synthesis process, the Mamdani inference synthesis algorithm is used. The formula for calculating the fusion membership degree of the Mamdani inference synthesis algorithm is shown in Equation (7):

$$U^* = \bigcup_{j=1}^{n} \left(S^* \circ R_j\right), \tag{7}$$

where S^* is the fuzzy subset of the degree of membership; R_j is the implication relation that is the corresponding fuzzy rule; $\circ$ represents the inference synthesis algorithm. In the actual calculation process, only the activated fuzzy rules are logically reasoned.

2.2.5. Defuzzification of Membership Degrees. The fuzed health indices are obtained by defuzzifying the membership degrees, which are the outputs of the inference synthesis process. Defuzzification can be achieved in a number of ways, such as the gravity center method, equal area method, and extreme value method. This paper intends to adopt the center of gravity method to achieve defuzzification.

$$H = \frac{\sum_{i=1}^{r} A_i H_i}{\sum_{i=1}^{r} A_i}, \tag{8}$$

where A_i is the membership degree corresponding to the inputs; H_i is the health index corresponding to the fuzzy health degree.

2.3. Health Status Assessment for System Level. Faulty components and healthy components have different effects on the health status evaluation of fluid loop systems. To objectively determine the weight of the health state of the components relative to the health state of fluid loop systems, the CRiteria importance through intercriteria correlation (CRITIC) weighting method is studied. The CRITIC weighting method is an objective weight determination method proposed by Diakoulaki et al. [29], which is suitable for the processing of

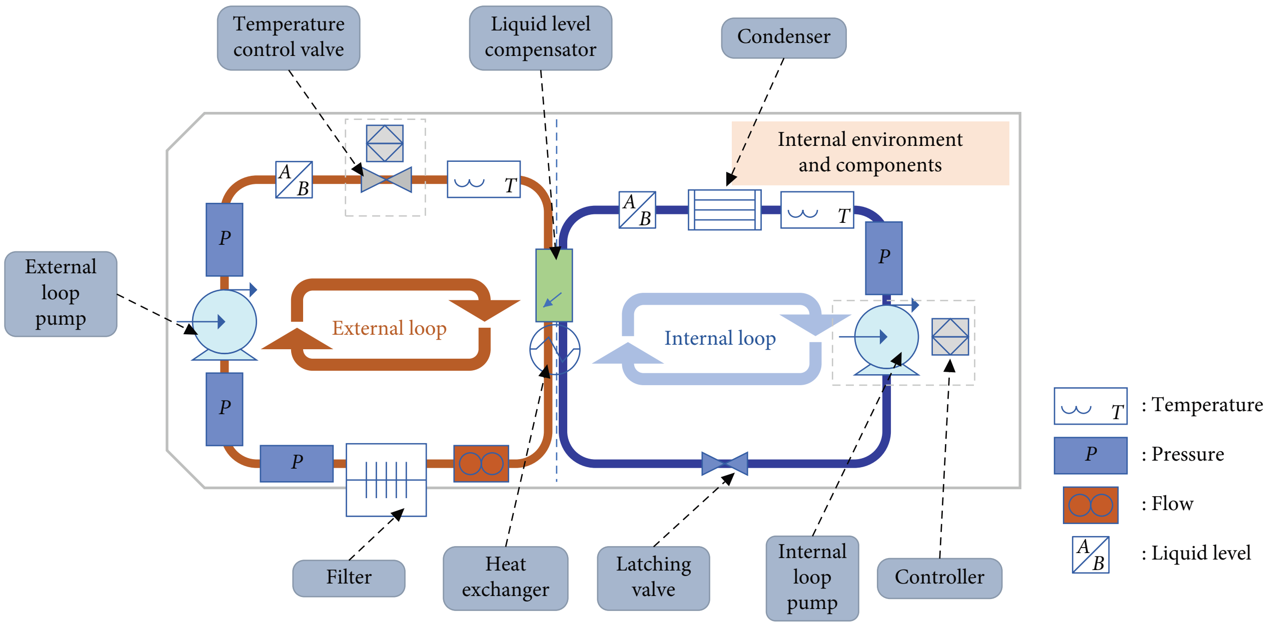


Figure 6: Structure of the experimental fluid loop system.

multi-index objective weights. The algorithm evaluates the information content of a single index and measures the difference in the information content of different indexes. The large difference of one index among all indices implies that the more information the index stores and the more weight it has. Therefore, this paper refers to the idea of the objective weighting method of CRITIC and designs a strategy for adaptive weight adjustment. According to the number of faulty components, the weight of faulty components is adaptively increased, and the weight of healthy components is decreased. The method is described as follows:

(1) The number of faulty components is counted and denoted as n. The health indices of all faulty components are denoted as $[m_{f1}, m_{f2}, \ldots, m_{fn}]$.
(2) The remaining healthy components are considered as a whole. The health indices of all healthy components are averaged and denoted as $\overline{m_h}$.
(3) Calculating the weights adaptively as $k = 1/(1 + 2n)$. This weight value is automatically adjusted with the number of faulty components.
(4) Calculating the system-level health index $m = \sum_{i=1}^{n} m_{fi} \cdot 2k + \overline{m_h} \cdot k$.

The above strategy is used to fuze all health indices at the component level and infers the system-level health index. The comprehensive health assessment of fluid loop systems is carried out to provide decision support for maintenance personnel.

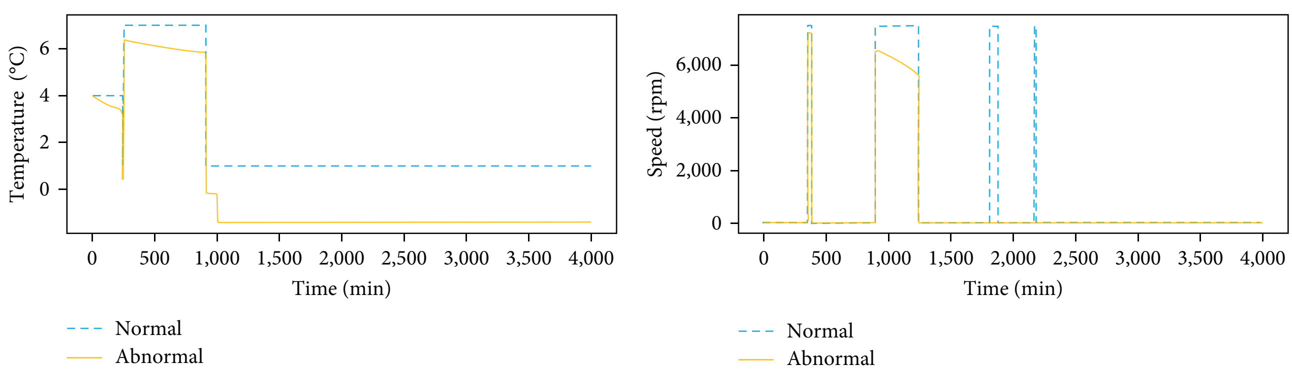
3. Experimental Verification

The proposed HMIF method is validated on an experimental fluid loop system. The structure of the fluid loop system is shown in Figure 6. The system is mainly composed of the external loop subsystem and the internal loop subsystem. The external loop subsystem is used to absorb heat from the system, and the inner loop subsystem is used to dissipate heat. The external loop subsystem and the internal loop subsystem are coupled by the liquid-level compensator and the heat exchanger. The main functional components of the system include pump, temperature control valve, radiator, condenser, etc. Many kinds of sensors are configured on components to collect the monitoring data during system operation. The data to be collected are mainly expressed as continuous variables, such as temperature, speed, pressure, flow rate, liquid level height, and so on, which are shown in Table 3. A diversity of trends is implied in the collected data, such as slow change, fast change, and step change. The failure of the external loop pump of the system is used as an analysis case to verify the effectiveness of the health assessment method. In reality, the impeller of the external loop pump is broken.

3.1. Evaluation of Indicator-Level Health Index. For the external loop pump component, the main monitoring data are motor temperature and pump speed. When the pump is abnormal, these two kinds of monitoring data will change greatly compared with the normal operation state. The variation forms of these two types of data are the most complex among all monitored data, and their curves are also the most representative. They were sampled once every minute for 4,000 min. The curves of the data are shown in Figure 7. Figure 7(a) shows the curves of motor temperature monitoring value when the external loop pump is in a normal state and an abnormal state. The blue dotted line represents the temperature of the motor in a normal state, and the orange solid line represents the temperature of the motor in an abnormal state. From Figure 7(a), it can be observed that the temperature in the abnormal state is always lower than that in the normal state. About 1,000 min later, the motor

Table 3: Collected data.

Id	Component	Monitoring data	Units	Trends
C_1	Pump	Motor temperature	°C	Slow change
		Pump speed	r/min	Fast change
C_2	Filter	Pressure difference	kPa	Step change
C_3	Heat exchanger	Liquid temperature	°C	Slow change
C_4	Latching valve	Pressure difference	kPa	Step change
		Angle displacement	rad	Fast change
C_5	Controller	Flow rate	L/min	Fast change
		Liquid level	mm	Slow change
C_6	Condenser	Liquid temperature	°C	Slow change
C_7	Liquid level compensator	Outlet temperature	°C	Slow change
		Liquid level	mm	Slow change
C_8	Temperature control valve	Angle displacement	rad	Fast change



(a) (b)

Figure 7: Curves of the indicators in the normal and abnormal states: (a) curves of the external loop temperature control value; (b) curves of the external loop pump speed value.

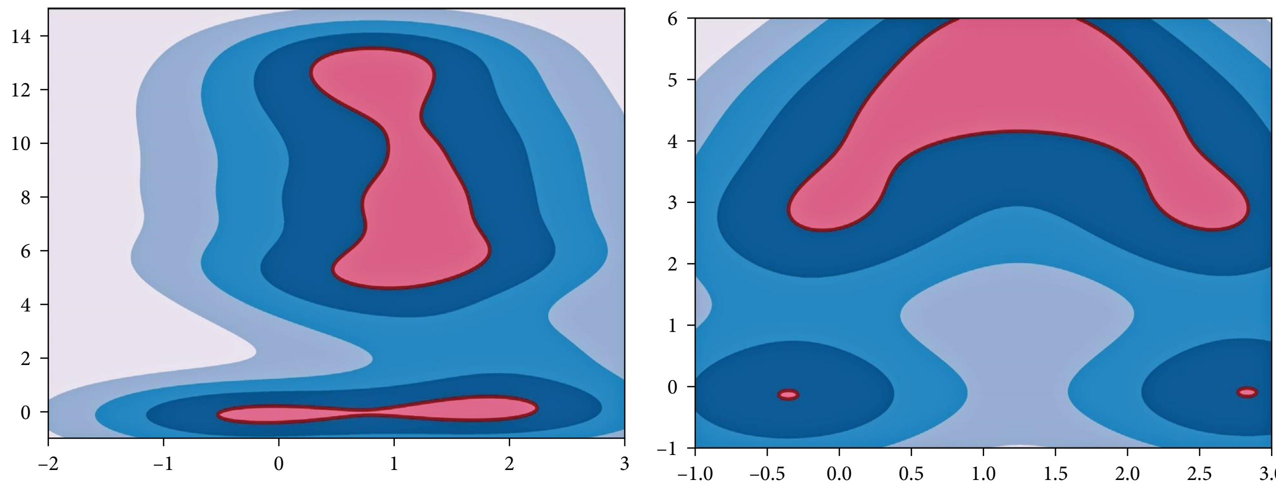
temperature in the abnormal state is even lower than 0°C. Figure 7(b) shows the pump speed of the external loop pump. The pump speed in the abnormal state has remained at 0 rpm after approximately 1,250 min.

Before calculating the feature distribution space, it is necessary to perform preprocessing on the data to eliminate the interference of random noise. The window function with the appropriate window length is selected to intercept the original data, and the mean and standard deviation of the intercepted data are calculated. Let the window function move to obtain a series of means and standard deviations. Two indicator sequences, i.e., moving average and moving STD, are obtained by preprocessing the original data of motor temperature and pump speed. These sequences are taken as the training set to construct the optimal distribution space, as shown in Figure 8. The dark red line in the figure represents the hyperplane. The pink area is the optimal normal distribution area. The other regions represent the potential anomaly distribution space.

The abnormal monitoring data are treated in the same way that normal data are processed. Then, the processed data are entered into the health assessment feature space, and the assessment results are shown in Figure 9. In Figure 9, the purple triangle points represent the detected abnormal indicators. The larger the number of samples in the normal area is, the higher the health degree of the sample is. When evaluating health status, it is necessary to calculate the ratio of the amount of indicators in the normal area to the total amount of indicators. That is, the probability of the data to be evaluated is in a healthy state. The probability is considered the health index. The total length of the two indicator sequences is 3,980. Among them, the number located in the health state distribution space of the two indicator sequences are 856 and 179, respectively. Therefore, the health index of motor temperature is 21.5, and the health index of pump speed is 4.5.

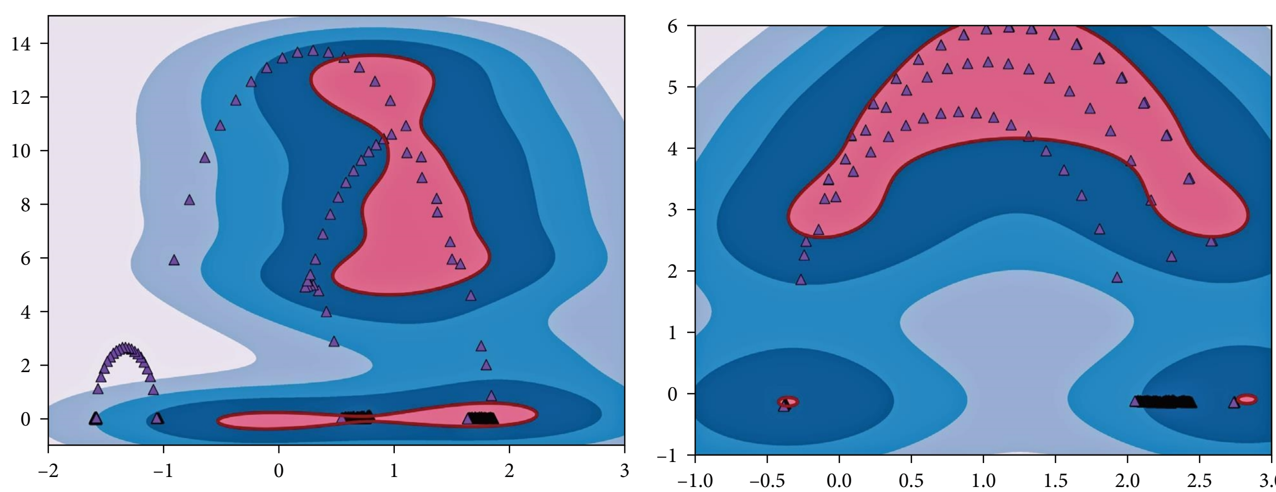
Other indicators of the experimental fluid loop system are processed according to the above health status assessment procedures. The evaluation results are consistent with the actual situation. The experimental results show that the health status assessment method is effective at the indicator level.

3.2. Evaluation of Component-Level Health Index. The fuzzy inference is utilized to fuze the health indies of the motor temperature indicator and the pump speed indicator. Membership functions and fuzzy rules also need to be



(a) (b)

Figure 8: Feature space of two indicators: (a) feature space of motor temperature; (b) feature space of pump speed.



(a) (b)

Figure 9: Evaluation results of two indicators: (a) evaluation result of motor temperature; (b) evaluation results of pump speed.

predetermined. The health state of components is divided into five degrees: healthy, degradation, severe degradation, hazard, and severe hazard, and represented as a set $H = \{h_1, h_2, h_3, h_4, h_5\}$. Therefore, the range of the health index of the components is uniformly divided into five intervals. These five intervals correspond to the domain of different membership functions. The membership functions of the five degrees are shown in Table 4, and the fuzzy rule base formulated based on expert experience is shown in Figure 10.

The health degree of the indicator level is mapped through the membership function set. The membership fuzzy subset of the motor temperature index after fuzzy mapping is $A = [0.425, 0.575, 0, 0, 0]$, and the membership fuzzy subset of the pump speed indicator after fuzzy mapping is $B = [1, 0, 0, 0, 0]$. According to the Mamdani algorithm, the fuzzy matrix of both is shown in Equation (9). Combined with fuzzy rules, the health degree corresponding to the fuzzy membership degree at the non-zero position in the fuzzy matrix is h_5, and the fusion membership is 0.575. That is, the health status of the pump is a severe hazard. Finally, the health index of the external loop pump is solved to be 18.5 by substituting the fuzed membership degree into the membership function corresponding to h_5.

$$S^* = A \wedge B = \begin{pmatrix} 0.425, 0, 0, 0, 0 \\ 0.575, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0 \\ 0, 0, 0, 0, 0 \end{pmatrix}. \tag{9}$$

The remaining components in the experimental fluid loop system are treated according to the above health status

Table 4: Membership functions for component-level evaluation process.

Degree	Membership function	Degree	Membership function
h_1	$A_{h_1}(x)=\begin{cases}0,\ x\in(0,\ 70)\\ \dfrac{x-70}{20},\ x\in[70,\ 90)\\ 1,\ x\in[90,\ 100]\end{cases}$	h_2	$A_{h_2}(x)=\begin{cases}0,\ x\in(0,\ 50)\&[90,\ 100]\\ \dfrac{x-50}{20},\ x\in[50,\ 70)\\ \dfrac{90-x}{20},\ x\in[70,\ 90)\end{cases}$
h_3	$A_{h_3}(x)=\begin{cases}0,\ x\in(0,\ 30)\&[70,\ 100]\\ \dfrac{x-30}{20},\ x\in[30,\ 50)\\ \dfrac{70-x}{20},\ x\in[50,\ 70)\end{cases}$	h_4	$A_{h_4}(x)=\begin{cases}0,\ x\in(0,\ 10)\&[50,\ 100]\\ \dfrac{x-10}{20},\ x\in[10,\ 30)\\ \dfrac{50-x}{20},\ x\in[30,\ 50)\end{cases}$
h_5	$A_{h_5}(x)=\begin{cases}1,\ x\in(0,\ 10)\\ \dfrac{30-x}{20},\ x\in[10,\ 30)\\ 0,\ x\in[30,\ 100]\end{cases}$	—	—

x_2 \ x_1	h_5	h_4	h_3	h_2	h_1
h_5	h_5	h_5	h_5	h_4	h_3
h_4	h_5	h_4	h_4	h_4	h_3
h_3	h_5	h_4	h_3	h_3	h_2
h_2	h_4	h_4	h_3	h_2	h_2
h_1	h_3	h_3	h_2	h_2	h_1

Figure 10: Fuzzy rule base.

assessment procedures. Except for the failure of the external loop pump, the rest of the components are in a healthy state. Experimental results show that the health assessment method is effective at a component level.

3.3. Evaluation of the System-Level Health Index. After the above calculation process, the health indices of all components are obtained as $[18.5, 87.2, 82.4, 90.0, 87.6, 86.5, 88.5, 90.0]$. According to the calculation rules of the adaptive weight algorithm, the mean value of the health indices of healthy components is $\overline{m_h}=87.5$, and the weight is $k=1/3$. The health index of the system level is calculated as $m=41.5$.

The health index of the experimental evaluation indicates that the fluid loop system is in hazard. The result is consistent with the expert evaluation conclusion. The experimental results show that the proposed health assessment method is effective for system-level assessment.

4. Discussion

There are differences in the likelihood and severity of different failures in fluid loop systems. The risk index matrix

Table 5: Risk index matrix.

	I	II	III	IV
A	1	3	7	13
B	2	5	9	16
C	4	6	11	18
D	8	10	14	19
E	12	15	17	20

(RIM) has been evaluated by the research and development institution of fluid loop systems based on a large amount of expertise to meet the health status assessment requirements. The severity of the fault represents the degree of damage to the entire fluid loop system if the fault occurs. There are four levels of severity, with the first level being the most severe and the fourth level being the slightest. The likelihood of occurrence indicates the frequency of failure, which is categorized into five levels. Level A indicates frequent occurrence, and level E indicates rare occurrence. The RIM is formulated by the likelihood of failure occurrence and the severity of the failure, as shown in Table 5. The fault risk evaluation index can comprehensively reflect the health state of fluid loop systems. The risk index in the range of 0 and 14 is defined as severe hazard, the range of 15 and 16 as hazard, the range of 17 and 18 as severe degradation, and the range of 19 and 20 as degradation. Therefore, the health state of fluid loop systems can also be analyzed according to the likelihood of fault occurrence and the severity of the failure.

The HMIF health status assessment method and RIM are used to evaluate the health status of 14 sets of monitoring samples of the experimental fluid loop system. The evaluation results are shown in Table 6. Compared with the evaluation results based on RIM, there are only two differences in the evaluation results of the HMIF method, namely, S_6 and S_{10}. The S_6 sample was evaluated as degradation by the RIM method, while it was evaluated as a severe hazard by the HMIF method. The S_{10} sample was evaluated as the severe

Table 6: Evaluation results of HIMF and RIM.

Sample	Severity	Likelihood of occurrence	Risk index	Results of RIM	Results of HMIF	Health indices
S_1	II	E	15	h_4	h_4	34.5
S_2	I	E	12	h_5	h_5	8.2
S_3	I	D	8	h_5	h_5	2.0
S_4	I	E	12	h_5	h_5	6.8
S_5	I	D	8	h_5	h_5	1.4
S_6	IV	E	20	h_2	h_5	13.4
S_7	III	E	17	h_3	h_3	52.8
S_8	II	E	15	h_4	h_4	32.3
S_9	II	E	15	h_4	h_4	36.7
S_{10}	III	E	17	h_3	h_4	33.3
S_{11}	II	E	15	h_4	h_4	37.8
S_{12}	III	E	17	h_3	h_3	49.6
S_{13}	III	E	17	h_3	h_3	48.4
S_{14}	III	E	17	h_3	h_3	48.8

degradation by the RIM method, while it was evaluated as the hazard by the HMIF method. After analysis, the evaluation results of the proposed method are very close to the results based on a large number of expert experiences, which verifies the feasibility of the HMIF method. In addition, the HMIF method also obtains the health degree and health index of each component in the fluid loop system, which shows that the method can reflect the health state of the whole system more scientifically and reasonably. In the absence of expert experience, the HMIF method proposed in this paper can accurately and reliably evaluate the health status of fluid loop systems.

5. Conclusions

In this paper, the HMIF method for health status assessment is constructed in view of fluid loop systems for long life and good performance requirements. The health index is defined to quantitatively evaluate the health state of fluid loop systems. The health assessment process of fluid loop systems in this method is divided into three levels, which are indicator level, component level, and system level. At the indicator level, One-Class SVM algorithm is used to obtain the distribution space under a normal state of indicators. The indicator-level health indices are evaluated by counting the number of indicators located in the health-state distribution space. At the component level, a health index evaluation process, which is based on fuzzy theory and expert experience, is proposed. At the system level, an adaptive weight adjustment strategy is proposed to fuze all component-level health indices. Finally, the HMIF method is verified by the health assessment of a practical fluid loop system. It can be concluded that the proposed method rightly evaluates the health status of the fluid loop system and provides a reference for system maintenance. However, a lot of prior knowledge is needed to construct the fuzzy rule base in the fuzzy evaluation of the component-level health state assessment. It brings inconvenience to the implementation of the method. The future work aims at further research to improve the application limitations caused by insufficient prior knowledge.

Data Availability

The data used to support the method of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the National Basic Research Project of China, grant number JCKY2019204C046.

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