



Research on Fault Intelligent Detection Technology of Dynamic Knowledge Network Learning System

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Abstract. The rapid development of computers has improved the scope of dynamic knowledge network learning applications. Online learning has brought convenience to people in time and place. At the same time, people began to pay attention to the efficiency and quality of online learning. At present, the network knowledge storage system is distributed storage system. The distributed storage system has great performance in terms of capacity, scalability, and parallelism. However, its storage node is inexpensive, and the reliability is not high, and it is prone to fault. Based on the designed fault detection model detection path, relying on building the knowledge data node fault detection mode, constructing the knowledge data link fault detection mode, completing the fault detection model detection mode, and finally realizing the dynamic knowledge network learning system fault intelligent detection technology research. The experiment proves that the dynamic knowledge network learning system fault intelligent detection technology designed in this paper reduces the fault rate of the network learning system by 37.5%.

Keywords: Network learning · Fault detection · Intelligent detection · Technology research

1 Introduction

Network learning advocates students as the main body, while intelligent network learning system is characterized by students' personalized learning [1]. The organization of domain knowledge and intelligent navigation are the basic problems to realize personalized learning in intelligent network learning system [2]. In this era of information explosion, learning determines its own competitiveness. However, many people spend a lot of time and money to enrich themselves through various channels. As a result, they find that what they finally master is fragmented information, which can not form a complete knowledge framework [3]. These isolated knowledge can not be used to solve practical problems, so it is particularly important to build a perfect knowledge learning system.

The dynamic knowledge network learning system jointly created by network technology, computer technology and communication technology has become an emerging learning method, providing the masses with convenient conditions for learning anywhere and anytime [4]. The storage system in the network learning system

is composed of multiple storage points, but multiple storage points are prone to data synchronization failure and serial effects [5]. When a virus invades one of the storage points, the relevant storage points may be implicated. Based on the above situation, the network learning system should adopt the fault intelligent detection technology to automatically detect the entire learning system before the network knowledge system fails, and find the place where the fault may occur, by backing up, copying, transferring, etc. the knowledge data. Which means to process the network learning system to ensure the integrity of the knowledge data and the security of the network learning system [6]. The experiment proves that the network learning system using the automatic fault monitoring technology can greatly reduce the fault rate of the system itself. In order to reduce the failure rate of dynamic knowledge network learning system, this paper proposes a new fault detection technology for dynamic knowledge network learning system.

2 Fault Detection Path Design of Dynamic Knowledge Network Learning System

The most common faults in dynamic knowledge network learning systems are data loss and data confusion. The system loses a lot of data and the system knowledge cannot be acquired normally.

Set the data loss rate of the dynamic knowledge network learning system as $u_k = Kx_k$, the following formula can be obtained.

$$\begin{cases} x_{k+1} = A_d x_k + (B_0 + DF(\tau_k)E)u_{k-d+1} + (B_1 - DF(\tau_k)E)u_{k-d} \\ y_k = Cx_k \end{cases} \tag{1}$$

Assuming the probability of data confusion is r , then:

$$P(\zeta_k = 0) = r, P(\zeta_k = 1) = 1 - r \tag{2}$$

If the estimated error of the state observation parameters of the dynamic knowledge network learning system is set as $e(k) = x(k) - \hat{x}(k)$, no data loss or confusion will occur. The state estimation error can be calculated by using the following formula:

$$e_{k+1} = Ae_k + BKe_{k-d+1} + B_1Ke_{k-d} + DFEKe_{k-d+1} - DFEKe_{k-d} \tag{3}$$

In the above formula, the following formula can be obtained by introducing the augmented vector $\theta_k = [x_k, e_k]^T$.

$$\begin{aligned} \theta_{k+1} = & \begin{bmatrix} A & 0 \\ 0 & A \end{bmatrix} \theta_k + \begin{bmatrix} (B_0 + DFE)K & 0 \\ DFEK & B_0K \end{bmatrix} \theta_{k-d+1} \\ & \begin{bmatrix} (B_1 - DFE)K & 0 \\ -DFEK & B_1K \end{bmatrix} \theta_{k-d} \end{aligned} \tag{4}$$

The following formula is used to represent the estimation error of state observation parameters in the case that data of dynamic knowledge network learning system cannot be obtained.

$$e_{k+1} = (A - LC)e_k + B_0Ke_{k-d+1} + B_1Ke_{k-d} + DFEKx_{k-d+1} - DFEKx_{k-d} \tag{5}$$

The fault detection path model of random switching control can be established by using the following formula:

$$z(k+1) = A(\xi_k)z(k) + A_3z(k-d+1) \tag{6}$$

The following state observation parameters can make the fault path detection model approach stable.

$$\xi(k+1) = \begin{bmatrix} \overline{A_{c11}} & \overline{B_{c1}} \\ 0 & I \end{bmatrix} \xi(k) + \begin{bmatrix} \rho(k+1) \\ 0 \end{bmatrix} + K(k) \tag{7}$$

$$[\lambda(k+1) - \overline{A_{c21}} \quad \overline{B_{c2}}] \xi(k)$$

In the above formula, $K(k)$ is used to describe the kalman filter increment.

According to the method described above, the fault detection path of dynamic knowledge network learning system is designed by using the residual of observation parameters. The detection path is shown in Fig. 1.

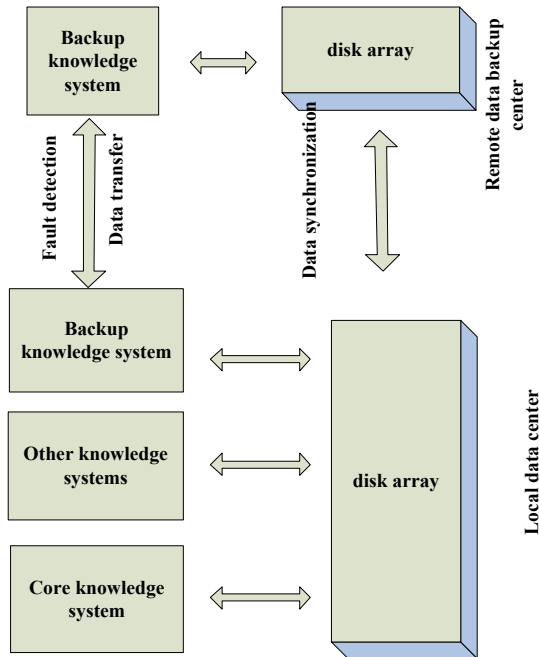


Fig. 1. Fault detection model detection path

The fault detection path ensures the security of the knowledge data in a single disk by copying and transferring [7, 8]. If the knowledge data in the storage system is lost, all knowledge acquisition in the entire network learning system cannot be performed normally [9]. Therefore, ensuring the security of knowledge data in the system is a top priority.

3 The Fault Detection Model of Dynamic Knowledge Network Learning System Is Constructed

In the dynamic knowledge network learning system, each operation execution time and system feedback time delay of acquiring knowledge are negligible [10]. The network learning system applies network technology to transmit knowledge information, and at the same time, the system has the possibility of fault [11].

3.1 Building Knowledge Data Node Fault Detection Mode

Let $G = (\pi, \Lambda)$ represent the network in the knowledge learning system, G is a vector, and $n = (1, \dots, n)$ represents the set of knowledge storage points in the knowledge learning system [12]. Then, $\Lambda \subseteq \pi \times \pi$ represents a collection of knowledge links in the knowledge learning system. Expressed as function [13]:

$$F_Y = F_X \times 2^\pi \quad (8)$$

Where F_Y is the value range of the knowledge system, F_X is the natural number set, and formula (1) represents the set of knowledge nodes. A indicates the set of storage node faults at a certain moment. If the input data produces set A , it indicates that the knowledge data node is not faulty, and the knowledge data is not lost in the storage system [14]. If the input data does not generate the set A , it indicates that the knowledge data node is faulty, and the corresponding knowledge data is lost. The dynamic knowledge network learning system will automatically detect the cause of the loss and synchronize the data in time.

3.2 Building the Knowledge Data Link Fault Detection Mode

The link refers to the path passed by the knowledge node in the network knowledge system. The two knowledge nodes belong to the neighbor relationship, and the network path from the m knowledge node to the n knowledge node is represented by

m-n, and the two adjacent relationship knowledge nodes in the knowledge system [15], using $\text{neighbor}(n)$ to represent its path set. There are two functions for the link between the node m and the n node, namely: $\text{send}_{m,n}(A)$ and $\text{receive}_{m,n}(A)$. The former is to pass the information A in the knowledge node m to the knowledge node n, if the knowledge node n receives the information A in the knowledge node m, then the knowledge node m passes the latter function to the knowledge point n [16]. Expressed by function:

$$y_m = \begin{cases} y_m, y_m \geq T_d \\ y_m - R, y_m \leq T_d \end{cases} \quad (9)$$

Where y_m is the information amount of the m node, T_d is the difference between the information amounts of the m node and the n node, and R is a natural integer. For the knowledge storage nodes m and n, under the premise that the m-n link is complete, the knowledge storage node m transmits information to the n through the link. If the $\text{send}_{m,n}(A)$ and $\text{receive}_{m,n}(A)$ functions are displayed in the system, it means that the link is not faulty, and the information won't be lost while transmitted in the link. If both $\text{send}_{m,n}(A)$ and $\text{receive}_{m,n}(A)$ functions are not displayed in the system, or only one [17] is displayed, it indicates that there is a problem between the two knowledge nodes, the dynamic knowledge network learning system will automatically monitor the cause of the problem and fix it in time.

3.3 Establishment of Intelligent Fault Detection Model

When a knowledge node or a link in the dynamic knowledge network learning system has problems, it will affect the normal operation of the knowledge learning system [18, 19]. The introduction of fault self-energy monitoring technology is mainly to automatically detect the entire learning system and find out where the fault may occur before the network knowledge system fails [20]. Before the fault occurs, the network learning system is processed by means of backing up, copying, and transferring the knowledge data to ensure the integrity of the knowledge data and the security of the network learning system [21, 22]. The fault detection algorithm is as follows:

Var Dp: //Fault detection module of initial process p;

Rp " π ": The initial process p has a corresponding timer for any of the processes in the set π ;

Initialization:

Dp= \varnothing ;

Forall q do rp " $q=\delta+v$ ";

Start sending process,send message with interval δ :

Forall q do send <alive> to q;

Receive process, q reset after receiving <alive> message:

Rp " $q=\delta+v$ ";

Detecte faults when rp " q " exceeds interval δ :

Dp=Dp \cup q

The fault detection technology is based on the delay of knowledge node information [23], δ is the transmission period of information fault detection, and the knowledge data node sends the <alive> message [24, 25] according to the δ period, if the response feedback message has not been received within a certain time, which indicates that the dynamic knowledge network learning system has failed (Fig. 2).

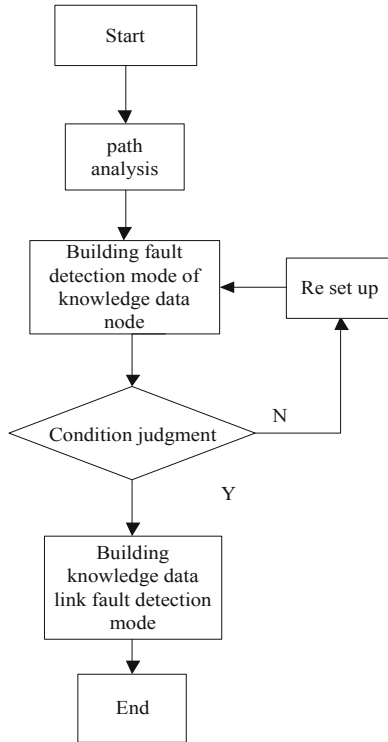


Fig. 2. Implementation process of intelligent detection model for network learning

Based on the fault detection model detection path design, the knowledge data node fault detection mode is built, the knowledge data link fault detection mode is built, and the network learning system fault intelligent detection model is realized.

4 Experimental Design and Result Analysis

In order to verify the effectiveness of the research on the fault intelligent detection technology of the dynamic knowledge network learning system proposed in this paper, the simulation test is carried out. During the test, two different dynamic knowledge network learning systems are used as test objects to test whether the system which gained knowledge per unit time failed. The knowledge data of two learning systems, English, mathematics, and physics are simulated. In order to ensure the accuracy of the simulation test, multiple simulation tests are performed, and the data generated by multiple tests are presented in the same data chart.

4.1 Data Preparation

In order to ensure the accuracy of the simulation test process and results, the test parameters are set. The simulation test uses two different dynamic knowledge network learning systems as the simulation test objects, simulates the number of system faults, and analyzes the simulation test results. Due to the amount of knowledge, the complexity of knowledge information, and the difficulty level of knowledge information contained in different stages and levels of knowledge data are different, the amount of correct knowledge is also different, and it has an impact on the test results. Therefore, it is necessary to ensure that the difficulty, subject and study time are consistent during the test. Set the tester's network learning time to 24 h. The test data setting results in this paper are shown in Table 1.

Table 1. Test parameters setting

Type	Complexity
Junior middle school	English
	Math
	Chemistry
	Physics
High school	English
	Math
	Chemistry
	Physics
University	English
	Chemistry
	Math
	Physics
Graduate student	English
	Math
	Chemistry
	Physics

4.2 Analysis of Test Results

The experimental results are counted as a contract collection schedule, and the test results are shown in Table 2.

Table 2. Number of system faults when acquiring knowledge

System type	Subject	Number of faults
Traditional system	English1	0
	English2	1
	English3	1
	English4	2
	Math1	1
	Math2	0
	Math3	1
	Math4	1
	Physics 1	0
	Physics 2	1
	Physics 3	1
	Physics 4	2
	Chemistry1	0
	Chemistry2	0
	Chemistry3	1
	Chemistry4	2
The system designed in this paper	English1	0
	English2	0
	English3	0
	English4	0
	Math1	0
	Math2	0
	Math3	0
	Math4	1
	Physics 1	0
	Physics 2	0
	Physics 3	0
	Physics 4	0
	Chemistry1	0
	Chemistry2	1
	Chemistry3	0
	Chemistry4	1

The numbers behind the subjects in the table indicate the difficulty of knowledge. The larger the number, the more complicated and difficult the relevant knowledge is. Because 12 different execution parameters are set during the test, it is impossible to obtain the experimental results at a glance, thus affecting the comparative analysis of the two systems. According to Table 2, the comparison of the number of faults of the system when acquiring knowledge is shown in Fig. 3.

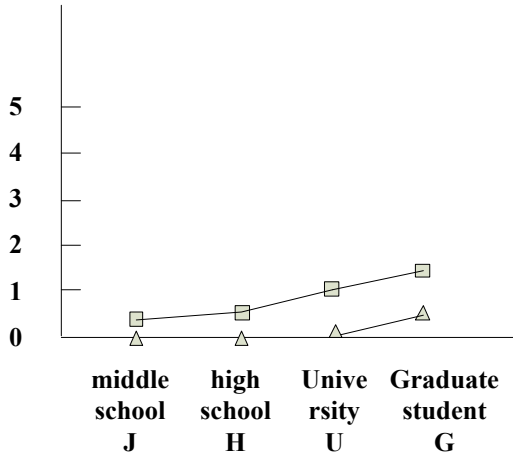


Fig. 3. Number of system faults when acquiring knowledge

In the figure, the abscissa is the degree of difficulty of knowledge, and the ordinate is the number of times the system fails when acquiring knowledge. The horizontal and vertical coordinate data are referred to Table 2. It can be seen from Fig. 3 that the dynamic knowledge network learning system fault intelligent detection technology research is significantly reduced compared with the traditional system.

In order to further verify the superiority of this method, the failure rate of dynamic knowledge network learning system is compared after the application of different methods. The results are shown in Table 3.

Table 3. System failure rates were compared by different methods

Number of experiment	Traditional system	The system designed in this paper
20	39.7%	0.6%
40	40.2%	0.9%
60	38.1%	0.5%
80	35.6%	1.0%
100	38.2%	0.4%
120	37.4%	0.6%
Average	38.2%	0.7%

As can be seen from the above table, the intelligent fault detection technology of dynamic knowledge network learning system designed in this paper reduces the failure rate of network learning system by 37.5%.

5 Conclusion

This paper proposes a research on intelligent detection technology for dynamic knowledge network learning system fault, based on the design of fault detection model detection path, relying on building knowledge data node fault detection mode, constructing knowledge data link fault detection mode, the construction of fault detection model detection mode is completed, and finally the fault intelligent detection technology studied in this paper is realized. The tests in this paper show that the research on fault intelligent detection technology is effective. It is hoped that the research of fault intelligent detection technology in this paper can provide a theoretical basis for the research of fault intelligent detection technology in dynamic knowledge network learning system.

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