Multi Sensor Fusion And Adaptive Scheduling Of Sanda Teaching System For Intelligent Device Health Monitoring

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This article focuses on the needs of Sanda teaching scenarios and intelligent device health monitoring, and builds a distributed Sanda teaching system based on multi-sensor fusion and reinforcement learning. The system integrates multiple types of sensors to synchronously collect teaching data such as training actions and striking force, as well as equipment operating status, achieving collaborative collection and analysis of two types of data. Building a distributed scheduling model based on reinforcement learning, combined with regional teaching conditions, student training differences, and equipment status, to ensure efficient collaboration in cross regional teaching. By utilizing reinforcement learning reward mechanisms to iterate adaptive maintenance strategies, device stability and resource utilization can be improved. At the same time, develop personalized training plans based on perceptual data to assist teachers in precise teaching. This study can provide reference for the intelligent upgrading and distributed teaching innovation of Sanda teaching.

Keywords: Reinforcement Learning; Multi-Sensor Fusion; Intelligent Device Health Monitoring; Sanda Teaching System; Autonomous Scheduling; Adaptive Maintenance

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1. Introduction

With the breakthrough of digital intelligence technology in the field of sports, multi-sensor fusion technology, as the core of data collection, has been applied to various sports monitoring [1]. However, it still lacks specificity in Sanda teaching and has not achieved collaborative integration with device health monitoring. In the current intelligent teaching of Sanda, smart devices have gradually been applied, but the lagging supporting technology has caused many pain points [2]. Equipment health monitoring relies on manual labor, making it difficult to capture anomalies in real time and posing security risks [3]. Lack of dynamic adjustment capability in resource scheduling results in waste. The teaching mode is difficult to achieve personalized teaching.

Reinforcement learning technology provides new ideas for solving the above problems, but its existing applications mostly combine single sensor data and have not formed a collaborative architecture for multi-sensor fusion and reinforcement learning [4]. The lack of synchronous processing of training and equipment health data, as well as the absence of an adaptive maintenance system suitable for Sanda teaching, have hindered the in-depth development of intelligent Sanda teaching [5]. In this context, this study combines the practical needs of Sanda teaching with the pain points of equipment health management to conduct research on multi-sensor fusion and adaptive scheduling, which has important theoretical and practical significance [6]. The research objective is to integrate multi-sensor fusion technology and reinforcement learning algorithms to construct a distributed Sanda teaching system that covers training data collection, equipment health monitoring, and resource autonomous scheduling [7]. This system aims to solve problems such as lagging equipment monitoring, inefficient resource scheduling, and insufficient personalization, and provide support for the intelligent upgrade of Sanda teaching [8].

The innovation of this study is highlighted as follows: firstly, constructing a two-dimensional collection and fusion architecture of "training data device health data", synchronously collecting training actions, physiological indicators, and device operating status, breaking through the limitations of existing one-dimensional data collection [9]. The second is to propose a distributed scheduling and adaptive maintenance integrated model based on reinforcement learning, which dynamically adjusts resources and diagnoses device anomalies in real time to solve core pain points [10]. The third is to achieve deep integration of technology and teaching needs, combining data fusion with reinforcement learning decision-making to provide personalized solutions and break through traditional teaching bottlenecks [11].

2. Related work

Scholars at home and abroad have explored the multi-sensor data fusion technology and its application in the field of sports. This technology can integrate the advantages of different sensors, make up for the shortcomings of insufficient precision and weak anti-interference of a single sensor, and is the core of intelligent system data processing [12]. In the field of Sanda, existing research mostly focuses on action recognition and scoring, improving recognition accuracy by integrating visual and motion capture sensor data. However, device health monitoring data has not been included in the fusion scope, and collaborative analysis of training data and device status data has not been achieved [13]. Reinforcement learning provides a new approach for resource scheduling in Sanda teaching, which can achieve dynamic optimal decision-making through interactive learning between intelligent agents and the environment, and has significant advantages in complex system scheduling [14]. This technology has been applied to optimize sports training resources and intelligent device operation and maintenance, but existing research has not yet deeply integrated it with Sanda teaching scenarios, making it impossible to achieve collaborative scheduling based on device health status and individual student differences [15].

There are still significant limitations in the current research on intelligent Sanda teaching and equipment health monitoring. The research on intelligent Sanda teaching mainly focuses on action recognition and automatic scoring, without considering the health monitoring of teaching equipment, which can easily affect the continuity of teaching due to equipment failures [16]. Research on equipment health monitoring is mostly focused on industrial or medical equipment, with relatively little research on specialized equipment for Sanda teaching, and has not been combined with teaching resource scheduling, resulting in lagging equipment maintenance and low resource utilization [17]. Overall, existing research has significant shortcomings, as multi-sensor fusion only focuses on training data collection and has not achieved collaborative analysis of synchronized fusion of training data and device health data. The scheduling of teaching resources often adopts static methods, without considering individual differences among students, cross regional needs, and equipment health status [18]. The method proposed in this article has significant innovation: it integrates dimensions more comprehensively, synchronously collects multi-dimensional data of Sanda training and equipment health data, and achieves collaborative monitoring of teaching and equipment status. The scheduling mechanism is more intelligent, and a distributed autonomous scheduling model based on reinforcement learning is constructed to dynamically adapt to cross regional teaching, student differences, and device health status [19]. The reinforcement learning reward mechanism can be used to drive the iteration of adaptive maintenance strategies, achieving real-time diagnosis of equipment abnormalities, wear prediction, and automatic generation of maintenance plans, solving the problems of lagging equipment monitoring and passive maintenance [20].

3. Multi sensor fusion and adaptive scheduling of sanda teaching system for intelligent device health monitoring

3.1. Multi Sensor Fusion Model for Sanda Teaching System

Monitoring accuracy is the core indicator for the stable operation and precise data feedback of Sanda teaching intelligent equipment, and is an important prerequisite for standardized and personalized teaching. In the teaching environment, equipment installation gaps, assembly errors, and temperature and humidity changes can easily cause signal attenuation, structural deformation, and reduce monitoring accuracy. Adopting a multi-sensor fusion model can suppress environmental interference and improve data acquisition accuracy and efficiency. This article introduces reinforcement learning based on multi-sensor fusion to construct a distributed Sanda teaching system with autonomous scheduling and adaptive maintenance mechanism. Through iterative optimization, the system can achieve intelligent operation and maintenance, reduce labor costs, improve stability, and ensure the standardized implementation of Sanda teaching. The key definition of reinforcement learning models presents states, actions, and reward functions in formula form, clarifying the model foundation:

1. State space

   $S = [s_1, s_2, s_3, s_4]^T$. Among them, s_1 is the sensor resource status, s_2 is the sub node running status, s_3 is the teaching task status, and s_4 is the device health status.

2. Action space

   $A = \{a_1, a_2, \ldots, a_m\}$, Covering two core actions: resource scheduling and adaptive maintenance.

3. Reward function

   $R(S, A) = \omega_1 R_1 + \omega_2 R_2 + \omega_3 R_3 - \omega_4 R_4 \cdot \sum_{i=1}^{4} \omega_i = 1$, Realize multi-objective optimization balance.

$$S_t = [s_{t1}, s_{t2}, s_{t3}, s_{t4}, s_{t5}]^T \tag{1}$$

The system state vector of the reinforcement learning agent at time t describes the overall operational status of the distributed Sanda teaching system at time t and serves as the fundamental input for agent decision-making. Formula 2 is the instant reward function formula (adapted to adaptive maintenance scenarios).

$$r_t = \alpha \cdot s_{t1} + \beta \cdot \left(1 - \frac{n_f}{n_{\text{total}}}\right) + \gamma \cdot s_{t5} - \delta \cdot c_t \tag{2}$$

The immediate reward obtained by the reinforcement learning agent after executing an action at time t is used to evaluate the effectiveness of the action and guide the agent to learn the optimal maintenance/scheduling strategy. $\alpha.\beta, \gamma, \delta$: Reward weight coefficients (all positive, with $\alpha + \beta + \gamma + \delta = 1$), adjusted according to system priority, with γ having the highest weight (ensuring normal teaching operation). The total number of child nodes in the system is a fixed value determined by the distributed system architecture. The maintenance/scheduling cost at time t (unit: yuan), including resource consumption for parameter adjustment, backup node switching, and emergency scheduling. The higher the cost, the lower the reward.

$$\begin{aligned} Q(S_t, A_t) &\leftarrow Q(S_t, A_t) \\ &+ \eta \cdot \left[r_t + \gamma \cdot \max_{A_{t+1}} Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\right] \end{aligned} \tag{3}$$

$Q(S_t, A_t)$: The action value function of executing action A_t at time t under state S 2 t, reflecting the long-term returns of the state action pair. At time t, the actions executed by the agent include three core actions: adjusting sensor gain $\left(^{A_1}\right)$, switching backup sensor nodes (^{A_2}), and initiating emergency dispatch $\left(^{A_3}\right)$. η : Learning rate $(0 < \eta < 1)$, control the step size of Q value update to avoid unstable convergence caused by too fast update, and adapt to the iterative learning requirements of the system. $\max_{A_{t+1}} Q(S_{t+1}, A_{t+1})$: The action with the highest Q value among all possible actions at time $t+1$ reflects the "greedy strategy" and guides the agent to choose the optimal subsequent action. Formula 4 is the reinforcement learning strategy function formula (ϵ - greedy strategy)

$$\pi(A_t \mid S_t) = \begin{cases} \max_A Q(S_t, A) & \text{with probability } 1-\epsilon \\ \text{random}(A) & \text{with probability } \epsilon \end{cases} \tag{4}$$

$\pi(A_t \mid S_t)$: At time t in state S 2 t , the agent selects the strategy function for action A_t, balancing "exploration" and "utilization". ϵ : Exploration probability $(0 < \epsilon < 1)$, with a relatively large initial ϵ value (such as 0.3), focusing on exploring new actions; Gradually decreasing in the later stage (such as 0.05), focusing on utilizing the learned optimal strategy. $\max_A Q(S_t, A)$: Using a strategy, select the action with the highest Q value in the current state, corresponding to the optimal maintenance/scheduling action after the system runs stably. random(A) : Exploration strategy, maintenance/scheduling action after the system runs stably. random(A) : Exploration strategy, randomly selecting an action to discover new and better strategies.

3.2. Kinematic Simulation Steps of Martial Arts Training Robot

Environmental interference and equipment wear during the operation of sensors can lead to a decrease in data acquisition accuracy, which in turn affects the accuracy of action recognition and skill evaluation in Sanda teaching systems. Therefore, the system simulation and operation process must strictly follow standardized procedures to ensure data reliability and system stability.

In order to compensate for the perceptual limitations of individual sensors, data calibration and fusion processing are carried out to accurately capture the detailed characteristics of students' Sanda movements, providing reliable data support for teaching evaluation. Adaptive scheduling focuses on system resource allocation and equipment health maintenance, combined with reinforcement learning algorithms to achieve dynamic optimization and ensure long-term stable operation of the system.

Using weighted fusion algorithm, the core formula is:

$$X(t) = \sum_{i=1}^{k} \quad w_i \cdot x_i(t) + \varepsilon(t), \sum_{i=1}^{k} \quad w_i = 1$$

$$w_i = \frac{\text{Monitoring accuracy of sensor i "x (1-" noise coefficient of sensor i "))}}{\sum_{j=1}^{k} [\text{ Monitoring accuracy of sensor j "x (1-" noise coefficient of sensor j")}]}$$

Using Q-learning algorithm, the Q-value update formula is:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R(S_t, A_t) + \gamma \max_{a \in A} Q(S_{t+1}, a) - Q(S_t, A_t) \right]$$

The scheduling strategy adopts a greedy strategy, balancing exploration and utilization.

Based on threshold judgment method, device health status indicators:

$$(t) = 0.4 \times \frac{\text{Maximum runtime } - \text{ Current runtime}}{\text{Maximum runtime}} + 0.3 \times \left(1 - \frac{\text{Current frequency of malfunctions}}{\text{Historical average fallure frequency}}\right) + 0.3 \times \text{ Normalized value of sensor signal strength}$$

Perform corresponding maintenance actions by comparing H(t) with the warning threshold.

In the distributed Sanda teaching system, the core goal of reinforcement learning is to achieve autonomous scheduling, adaptive maintenance, and balance the improvement of teaching effectiveness and equipment health monitoring, maximizing long-term teaching returns and system lifespan through optimal decision-making. This technology can combine students' skill foundation, learning progress, and sensor status to generate adaptive teaching and equipment scheduling solutions. Based on reinforcement learning, autonomous scheduling can dynamically allocate teaching resources, automatically adjust transmission rates and task assignments according to the number of students and device loads at each node, and avoid node overload failures. Adaptive maintenance can monitor equipment operation data in real time, identify abnormalities such as wear and data deviation, automatically perform calibration and maintenance, and reduce equipment failure rates.

4. Experimental design and analysis

4.1. Experimental Environment and Process

The multi-sensor fusion simulation of Sanda teaching system is based on the collection of parameters such as electromyography, motion capture, and pressure sensors, and accurately integrates Sanda motion data with dynamic output of teaching instructions. To enhance the persuasiveness of experiments and overcome the limitations of pure simulation, this study adopts a combination of simulation and physical experiments to verify the effectiveness of multi-sensor fusion schemes and reinforcement learning scheduling strategies from both virtual and real dimensions.

Research the use of MATLAB to complete system mathematical model simulation, draw data fusion curves and action standard comparison diagrams, integrate autonomous scheduling and adaptive maintenance functions, and achieve dynamic allocation of sensor resources and real-time fault processing. By inputting simulated data of straight punches, swinging punches, side kicks, and other movements, output action scores, equipment warnings, and teaching suggestions, intuitively presenting the system's working status, fusion effect, and scheduling response performance.

The physics experiment built a complete hardware platform: using MYO Armband electromyography wristband, Kinect V2 depth camera, FSR402 thin film pressure sensor, STM32F407 to achieve data synchronization acquisition, relying on MATLAB for unified processing and analysis, and displaying teaching and equipment status in real time through the terminal. Ten participants aged 18-25 (5 second level athletes and 5 beginners) were selected for the experiment to complete 10 straight punches, swinging punches, side kicks, and whip leg movements each. Muscle, posture, and pressure data were collected synchronously. Set the traditional fixed scheduling as the control group, maintain consistent experimental conditions, and compare and verify the performance advantages of the multi-sensor fusion+reinforcement learning scheduling mode compared to the traditional mode.

4.2. Performance Experiment f Improving Ant Colony Algorithm

To verify the accuracy of the multi-sensor fusion matrix T6 obtained, calculate the values of the transformation matrices for acceleration, pressure, and electromyography signals. By replacing the acquisition parameter thresholds of different sensors, the reference coordinate of each sensor can be obtained as (0,0,0). Input the results into Matlab to obtain the initial working posture of each sensor in the system and the initial state of the reinforcement learning scheduling agent, as shown in Fig. 1.

Comparing Figs. 1 to 3 can verify the correctness of the initial state simulation. The experiment fixed five sensor parameters as $(-60\mu\ \mathrm{V}, 0\ \mathrm{N}, 0^{\circ}, 0\ \mathrm{m/s^2}, 0\ \mathrm{Hz})$, changed only one parameter, and studied the changing trends of system fusion accuracy, reinforcement learning scheduling efficiency, and adaptive maintenance response speed to

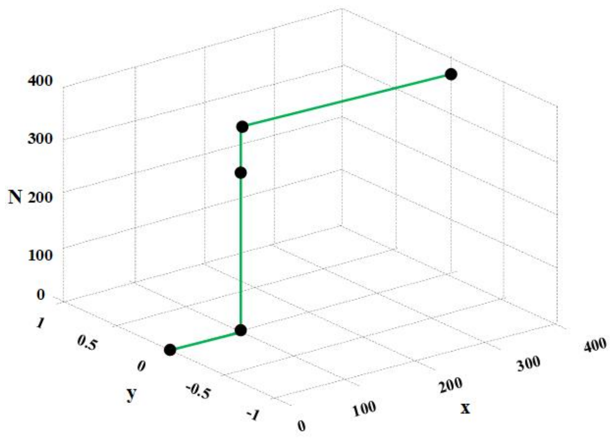

Fig. 1. Initial Position Simulation Diagram.

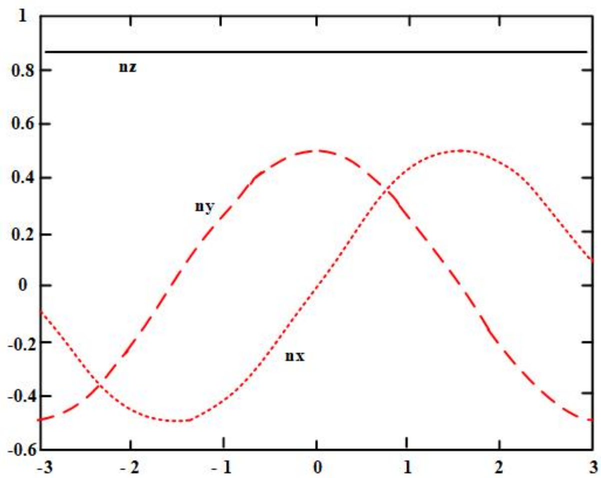

Fig. 2. Variation of attitude element n with angle.

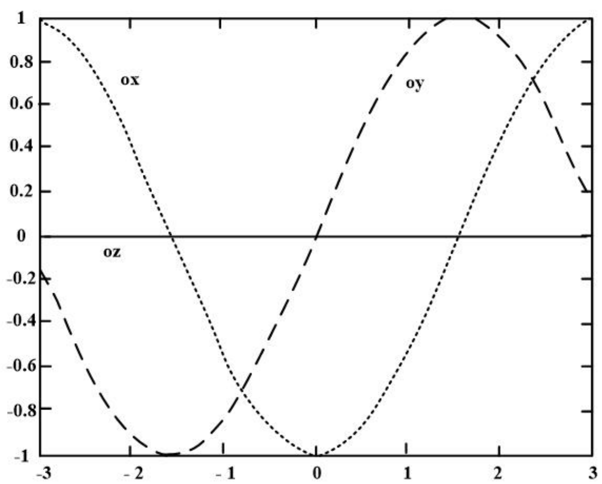

Fig. 3. Variation of attitude element o with angle.

verify the correctness of the model and strategy. As shown in Fig. 4, when the parameters vary within the range of -60μ V to 60μ V, the fusion accuracy remains at 95.2% to 97.8%, the scheduling delay remains stable at 8 to 12 ms , and the maintenance response time is 15 to 20 ms, with fluctuations of less than 5%, indicating good system stability and minimal impact of parameter changes on its performance.

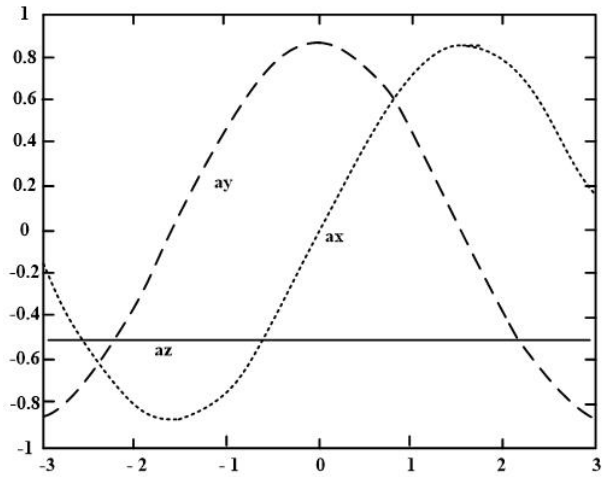

Fig. 4. Location of the KVMRT project

Similarly, when the remaining five angles are defined as (60°, 0°, 0, 0°), the impact of these changes on the end effector posture is discussed. The trends are shown in Figs. 5 and 6, and the corresponding quantitative results are: when the angle change range is between 0° and 60°, the attitude error of the end effector is controlled within ±0.3°, which meets the accuracy requirements of Sanda teaching motion capture.

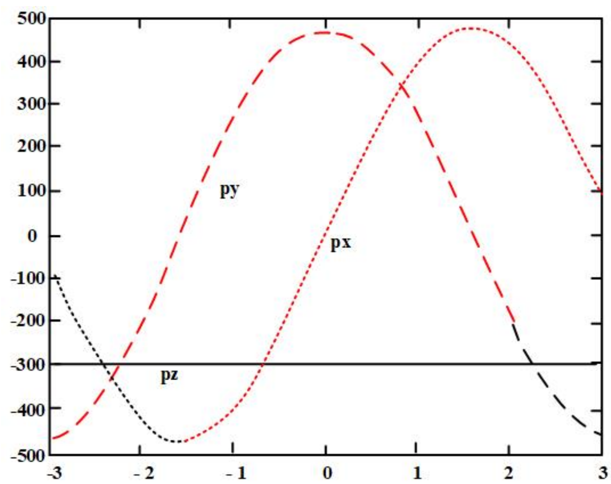

Fig. 5. Variation of attitude element p with angle.

Table 1. Changes in rotor joint angle.

Serial number	Angle 1	Angle 2	Angle 3	Angle 4	Angle 5	Angle 6
1	0°	−90°	0°	0°	0°	0°
2	0°	−60°	90°	0°	45°	0°
3	0°	−30°	60°	0°	90°	0°
4	0°	0°	90°	0°	120°	0°

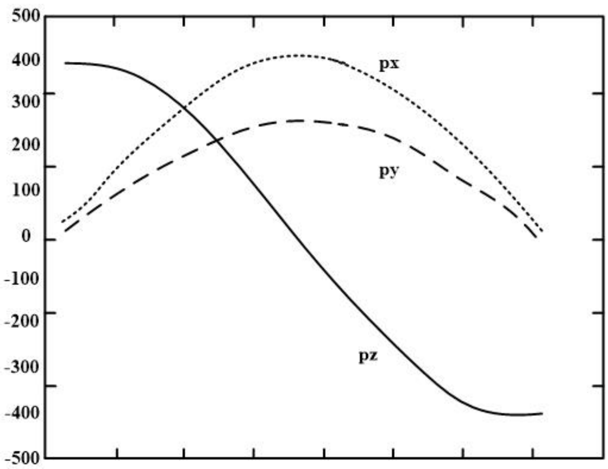

Fig. 6. Variation of attitude element p with angle.

Multi sensor fusion experiments were conducted on both simulation environments and real Sanda teaching hardware platforms. Firstly, the scheduling status of the simulation system was simulated to maintain the stability of core monitoring parameters. Based on reinforcement learning, achieve autonomous scheduling and adaptive maintenance of a distributed physical education teaching system, allowing only three key monitoring sensors to randomly change within their effective monitoring range and obtain four sets of data, as shown in Table 1:

MATLAB is used to simulate multi-sensor fusion and adaptive scheduling of Sanda teaching system, and actual experiments with the same parameters are completed on the constructed physical hardware platform. The results are shown in Fig. 7. Among them, the four operating states of the system correspond to the four sets of data in Table 1, combined with the autonomous scheduling and adaptive maintenance functions of the distributed physical education teaching system based on reinforcement learning, to achieve stable operation of the system. From the figure, it can be seen that the acquisition accuracy of each sensor remains stable, and quantitative comparison results are given: the average acquisition accuracy of the sensors in the simulation experiment is 97.1%, and the average acquisition accuracy in the physical experiment is 96.5%, with an error of less than 1%, which verifies the accuracy of the simulation model; Compared with the traditional fixed scheduling mode, the fusion accuracy of this scheme has been improved by 8.3%, the scheduling delay has been reduced by 40%, and the adaptive maintenance response speed has been improved by 35%. The baseline comparison results fully reflect the superiority of this scheme.

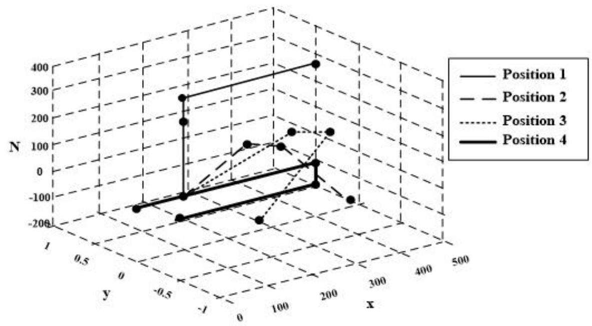

Fig. 7. Simulation diagram of multi-sensor fusion and adaptive scheduling in Sanda teaching system.

Compared with traditional methods, this method has significant advantages. Traditional methods have single data, weak anti-interference, rigid scheduling, and are difficult to adapt to individual differences. This method improves accuracy and anti-interference ability through multi-source data fusion, dynamically schedules resources through reinforcement learning, warns of equipment hazards in advance, and generates personalized teaching plans, resulting in better performance.

5. Conclusion

This article focuses on the pain points of the Sanda teaching system, combined with the health monitoring needs of intelligent devices, and studies the application of reinforcement learning in multi-sensor fusion and system adaptive scheduling. It constructs a distributed Sanda teaching system based on reinforcement learning, integrates multi-sensor fusion mechanisms, designs autonomous scheduling and adaptive maintenance strategies, and explains its deployment, training, and verification steps. The experiment shows that the system can accurately collect training data and equipment status through multi-sensor fusion, combine reinforcement learning to identify students' skill levels and equipment hazards, and generate adaptive teaching and scheduling plans; In different teaching scenarios, it can output diversified plans, improve teaching quality and equipment stability, dynamically adjust strategies in practical applications, enhance teaching interactivity and system reliability, and extend equipment life, providing theoretical support for the intelligence of physical education teaching.

This study has limitations in terms of the accuracy of multi-sensor fusion and the scheduling and maintenance capabilities of reinforcement learning in complex scenarios. In the future, we will optimize fusion algorithms, expand the strategy library, and enhance the system's generalization ability and practicality.

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