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A Method for Arranging Cheerleading Formations for College Cheerleading Teams Using Shortest Path Algorithms in Multi-Agent Environments

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Abstract In the current higher education system, physical education is faced with the development needs of integrating traditional teaching mode with modern technology. This paper proposes a multi-intelligent dynamic design method for college cheerleading that integrates the shortest path algorithm and reinforcement learning. The study adopts the MAPPO algorithm improved based on noise assistance to construct a multi-intelligence collaborative path planning model, and conducts training in a simulation environment with a side length of 10 m. The maximum speed of the intelligences is set to 0.90 m/s, and the learning rate is 0.003. The effect of the algorithm is verified through a comparative experiment with 102 students from a teacher training college in a certain city. The experimental results show that the students in the experimental class significantly improved in the four dimensions of movement technology, emotional expression, formation transformation and overall presentation, in which the emotional expression improved the most to reach 15.81 points, and the movement technology posttest score of 86.24 points was significantly higher than that of the control class of 78.23 points. The improved algorithm performs well in intelligent body collision rate control, with the CBRS value stably controlled near 1 and the CBRO value maintained in the range of 0.5-2.0. The study proves the effectiveness of reinforcement learning and path planning algorithms in cheerleading teaching, and provides a new technical path and theoretical basis for physical education intelligence.

Index Terms Cheerleading, Multi-intelligence, Reinforcement learning, Path planning, Cooperative control, Dynamic design

I. Introduction

Cheerleading is a kind of collective sports and fitness activities, which integrates various elements such as dance, running, gymnastics, fitness and so on, and is a high-intensity, high-energy, art and sports combined sports program [1], [2]. With the popularization and development of cheerleading sports in recent years, more and more colleges and universities have begun to set up cheerleading teams one after another, so that students can feel the passion, experience the joy, exercise and show themselves in the team [3], [4]. With the development and application of artificial intelligence, it promotes the realization of multi-intelligent dynamic design and collaborative control of college cheerleading, in which the integration of shortest path algorithm and reinforcement learning plays an important role [5].

The shortest path algorithm is a class of algorithms used to solve the shortest distance and lowest cost route, it is one of the very important applied algorithms, the algorithm aims to find the shortest path between two vertices in some graph-like (GG) network, which must be suitable for some kind of shortest path algorithms, and if the GG network can't be easily solved, the network can still be enlarged by a certain proportion so as to make it meet the shortest path solution requirements [6]-[9]. Reinforcement learning is an algorithm in the field of machine learning that learns optimal behavior through interaction with the environment. The core idea of reinforcement learning algorithms is to learn through trial and error and continuously adjust their strategies to maximize the cumulative reward. The integration of shortest path algorithms and reinforcement learning in college cheerleading is mainly reflected in cheerleading creation and collective movement synergy [10]-[13]. With the support of intelligent algorithms, it can improve the efficiency of cheerleading choreography, improve the quality of performance, and create a free and personalized cheerleading learning platform for students who are restricted by various time and conditions, so as to create conditions for the development of students' fitness, bodybuilding, health, and interest across time and space [14]-[17].

This study adopts the technical route of integrating shortest path algorithm and reinforcement learning to construct a multi-intelligence dynamic design system for college cheerleading. Firstly, a multi-intelligent reinforcement learning theoretical framework is established, and the cheerleading formation transformation problem is transformed into a multi-intelligent cooperative path planning problem. Then, a noise-assisted improved MAPPO algorithm is proposed to solve the problems of unclear credit allocation and overfitting in the traditional algorithm by introducing Gaussian noise mechanism. Then simulation experiments are designed to verify the performance of the algorithm and test the obstacle avoidance ability and goal arrival rate of the intelligences in a dynamic obstacle environment. Finally, the application effect of the algorithm in cheerleading teaching is verified through actual teaching comparison experiments in colleges and universities to provide technical support and practical guidance for the intelligent development of physical education.

II. New developments in high school cheerleading

II. A. Cheerleading in High Schools

II. A. 1) Teaching Value of Cheerleading Programs in Colleges and Universities

Cheerleading sport has a long history and contains rich cultural connotations. Cheerleading class in colleges and universities can cultivate college students' firm will quality and good aesthetic sense, promote quality education, activate the school atmosphere, enrich the amateur cultural life of college students, and make college students more energetic and positive [18].

(1) Cultivate college students' firm will quality and good aesthetic sense.

Compared with their revolutionary predecessors, college students in the new era have problems such as weak sense of independence, lack of hard work and the spirit of hardship and simplicity. The mastery of cheerleading technical movements requires college students to pay a lot of brain power, physical strength and time, and college students need to overcome many difficulties, so it can cultivate the good will quality of college students.

Cheerleading courses in colleges and universities seize the characteristics of young students' love of dance, and consciously cultivate college students' firm will quality and the spirit of learning and practicing hard through the study of cheerleading courses. Compared with other sports, cheerleading has beautiful movements and strong music, which can give the audience a beautiful enjoyment. The study of cheerleading courses in colleges and universities can improve the aesthetic sense of college students, so that college students can show the beauty of the body while exercising.

(2) It helps to promote the development of quality education.

Compared with other sports programs, cheerleading has no physical confrontation and pays more attention to students' personal physical and mental development and growth. It allows students in the cheerful and bright music accompaniment, not only can exercise, but also can cultivate students' aesthetic awareness and aesthetic ability, release the pressure and trouble in life, so it can promote the overall development of college students, in line with the requirements of quality education.

II. A. 2) Factors Related to the Development of Cheerleading in Colleges and Universities

(1) The degree of importance attached to cheerleading in colleges and universities

Whether cheerleading can be successfully developed and promoted in colleges and universities depends directly on the importance of the school to this sport. As a collective large-scale sports program, cheerleading sports in colleges and universities need to provide sufficient material support and economic support. At present, the study funds are limited, and the funds used for the development of sports programs are extremely tight. Compared with cheerleading, colleges and universities pay more attention to the development of track and field, basketball and other sports programs. Therefore, the equipment and funds can not meet the needs of the smooth development of cheerleading sports, can not effectively carry out the promotion of cheerleading sports and teaching activities, resulting in cheerleading sports training goals can not be achieved.

(2) Training resources for cheerleading in colleges and universities

The support of corresponding training resources and teaching resources is the guarantee for the smooth development of cheerleading sports in colleges and universities. Some college physical education teachers are unable to effectively apply the relevant professional training methods in the process of cheerleading training. There are loopholes in the judging standards and rules of cheerleading competitions in some colleges and universities, which is one of the main reasons for lowering the standard of cheerleading training. At the same time, the cheerleading training in many colleges and universities does not have professional and rich theoretical knowledge as a guide, and in the popularization and promotion of cheerleading, there is no systematic exploration of the exercise system of cheerleading in colleges and universities, and there is no optimization of the training methods of cheerleading. The effective allocation of teaching resources, the practicality of teaching methods and the diversification of teaching activities have an adverse effect on the effective allocation of teaching resources and the diversification of teaching activities, which can not effectively improve the efficiency of cheerleading sports.

II. B.Digital Technology Enables Innovative Teaching of Cheerleading in Colleges and Universities

The application of digital technology in the field of education has broken the traditional mode of instruction in colleges and universities, making college teaching more flexible and contemporary.

For one thing, it creates a platform for sharing curriculum resources and realizes the balanced development of the curriculum. The establishment of a digital platform through digital technology can make teaching resources easier to share and update, and teachers and students can quickly access teaching content and information. Through the resource sharing platform, the resource barriers of university education and even professional training institutions are broken down, and mutual exchanges and learning between schools and schools, schools and enterprises are promoted.

Secondly, open teaching content and flexible learning mode. Integrate the learning content of cheerleading, microclasses, teaching key points and other resources, and build a cheerleading learning and exchange platform through the digital platform to realize keyword retrieval, big data tracking and other functions, and push the relevant learning content to help students accurately locate the key points and difficulties of learning, and master the correct technical movements of cheerleading.

II. C.Difficulties in implementing the reality of digital technology

The application of digital technology in cheerleading programs is becoming more and more common, such as analyzing learning effects through video analytics software or using online platforms for remote training. However, some of the infrastructure applications are costly, and the application of AI technology needs to be supported by relevant equipment, software and talents, all of which require certain costs. Especially for some smaller schools, they may lack the corresponding financial and technical support to bear the corresponding application costs. In addition, intelligent equipment also requires regular maintenance and updating, and the high cost of equipment maintenance is also one of the obstacles to intelligent transformation.

While creating great opportunities for education, digital technological change has also brought imbalances to the continuously expanding development of different regions, the most prominent manifestation of which is the widespread existence of the digital divide. The application of digital technologies requires a certain level of technical foundation and skills, which may be a challenge for some teachers and students who are not familiar with digital technologies. In addition, digital technologies are updated at a very fast pace, which means that teachers and students need to continuously learn and adapt to new technologies in order to effectively utilize digital teaching tools and platforms, which undoubtedly increases their burden.

II. D.The Implementation Path of Cheerleading Teaching in Colleges Empowered by Digital Technology

Improving the digital infrastructure of colleges and universities is the foundation for realizing digital education. Schools can set up a digital technology department responsible for building a well-functioning digital platform. The platform should have basic functions such as course management, teaching resource management, student management, data analysis, etc. It can support teachers in online teaching and counseling, and can also meet the needs of students' independent learning. A special R&D team should be set up to be responsible for the continuous updating and functional upgrading of the platform, so as to keep pace with the times and respond quickly to market changes and user needs. Regularly release version updates and security patches to keep the platform advanced and safe. Optimize the user experience mechanism, follow the principle of optimization and simplicity, so that students can quickly and directly enter the platform to learn. Conduct user acceptance research, collect feedback and iteratively improve product design.

III. Multi-intelligent Dynamic Design Path Planning Algorithm for High School Cheerleading

III. A. Reinforcement of learning concepts

Reinforcement learning is a field in machine learning that emphasizes how an intelligent body takes a series of actions in its environment to maximize cumulative rewards. Intelligent bodies learn optimal strategies by interacting with the environment and learning based on reward signals fed back from the environment. Intelligentsia in reinforcement learning learn by trial and error in an exploration-exploitation trade-off. Reinforcement learning can be described as a Markov Decision Process (MDP) [19].

The MDP is defined by a quintuple (S, A, P, R, γ), where: S is the state space that represents the set of all states that the intelligence is in in the environment. In the university teaching network intrusion detection scenario, states can be represented as parameters such as network traffic characteristics, connection status, etc.

A is the action space, which is the set of all possible actions that the intelligent body can take in each state. For the intrusion detection model, the actions include classifying the network connection as normal or intrusion, or adjusting the detection threshold, etc.

P is the state transfer probability matrix, $P\left(s^{'}|s,a\right)$ represents the probability of transferring to state s after executing action a in state s, i.e., the likelihood that the state of the environment will change after the intelligent body takes an action.

R is the reward function and $R\left(s,a,s^{'}\right)$ gives the reward value obtained by the intelligent body when it performs action a in state s and transfers to state s. In intrusion detection, the intelligence should receive a positive reward if the intrusion is correctly detected and a negative reward for false or missed alarms.

γ is the discount factor, which determines the importance of future rewards. The closer γ is to 1, the more the intelligent body values long-term rewards. The closer γ is to 0, the more the intelligent body focuses on immediate rewards, which takes a value range of $0 \le \gamma \le 1$.

III. B. Basic Concepts of Multi-Intelligent Body Reinforcement Learning

The work in this paper is dedicated to solving fully collaborative multi-intelligentsia tasks, which are often formalized as Decentralized Partially Observable Markov Decision Processes (Dec-POMDP).

It can be represented as a tuple $G = \langle N, S, U, P, r, Z, O, \gamma, d \rangle$, where $N = \{1,...,n\}$ is the set of agents, n is the number of intelligences, d is the initial state distribution, $\gamma \in [0,1)$ is the discount factor, S represents the finite state space, and $U = \prod_{i=1}^{n} U_i$ is the joint action space.

At each time step, each agent $i \in N$ obtains its own local observation o^i based on the current observation function $O(s,i): S \times N \to Z$ and obtains the next action to be taken based on its own policy $\pi^i(\cdot \mid o^i)$. $u^i \in U^i$ The actions of all agents together form a joint action $u = (u^1,...,u^n) \in U$, after which it interacts with the environment. The next state is obtained according to the state transfer function $P(s^{'} \mid s,u)$ and the reward is obtained according to the shared reward function $r(s,u)$.

For representational convenience, we define the marginal state distribution as $\rho_\pi \triangleq \sum_{t=0}^{\infty} \gamma^t Pr(s_t = s \mid d, \pi)$ in this paper, where $Pr(s_t = s \mid d, \pi)$ denotes the state distribution at time step t using the joint strategy π under the initial state distribution d. The goal of reinforcement learning is to maximize the cumulative discounted expected reward:

$$J(\pi) = E_{s \sim \rho_\pi, u \sim \pi}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, u_t)\right] \tag{1}$$

Definition $i_{1:m} = (i_1, ..., i_m)$ is a set in which each element represents the serial number of the intelligences in any order, and $-i_{1:m}$ denotes its complement. The multi-intelligent body state action value function is:

$$Q_\pi^{i_{1:m}}(s, u^{i_{1:m}}) \triangleq E_{u_0^{-i_{1:m}} \sim \pi^{-i_{1:m}}, s_{1:\infty} \sim P, u_{1:\infty} \sim \pi}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, u_t) \mid s_0 = s, u_0^{i_{1:m}} = u^{i_{1:m}}\right] \tag{2}$$

The multi-intelligent body state value function is:

$$V_\pi(s,u) \triangleq E_{s_{1:\infty} \sim P, u_{0:\infty} \sim \pi}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, u_t) \mid s_0 = s\right] \tag{3}$$

The dominant value function can be induced as:

$$A_{\pi}^{i_{1:m}}(s,u^{i_{1:m}}) \triangleq Q_{\pi}^{i_{1:m}}(s,u^{i_{1:m}}) - V_{\pi}(s,u) \tag{4}$$

$$A_{\pi}^{i_j}(s,u^{i_{1:j-1}},u^{i_j}) \triangleq Q_{\pi}^{i_{1:j}}(s,u^{i_{1:j}}) - Q_{\pi}^{i_{1:j-1}}(s,u^{i_{1:j-1}}) \tag{5}$$

For simplicity, functions without superscripts are global-valued functions, e.g., $A_{\pi}(s,u) \triangleq A_{\pi}^{i_{1:n}}(s,u^{i_{1:n}})$. From the above two equations, the following decomposition theorem for multi-intelligencer dominant-valued functions can be deduced:

$$A_{\pi}^{i_{1:m}}(s,u^{i_{1:m}}) = \sum_{j=1}^{m} A_{\pi}^{i_j}(s,u^{i_{1:j-1}},u^{i_j}) \tag{6}$$

III. C. Deep Reinforcement Learning-based Collaborative Path Planning for Multi-Intelligents

In order to solve the problems of unclear credit allocation and policy overfitting in the existing multi-intelligence body algorithms, a noise-assisted MAPPO-based algorithm is proposed.

III. C. 1) Distributed PPO Algorithm

IPPO is the application of PPO algorithm to multi-intelligent body systems through distributed learning. In this multi-intelligent body system, each intelligent body has its own value function and policy network, which is independent from other intelligences.

The objective functions of the intelligences individually are learned through PPO. Intelligent body i distributed strategy is π_{θ}^{i}, where each intelligent body's separate strategy objective function is updated as follows:

$$J^i(\theta) = E_t\left[\min\left(\frac{\pi_{\theta}^i(a_t^i \mid s_t^i)}{\pi_{\theta_{dd}}^i(a_t^i \mid s_t^i)} A_t^{\pi_\theta}, clip\left(\frac{\pi_{\theta}^i(a_t^i \mid s_t^i)}{\pi_{\theta_{dd}}^i(a_t^i \mid s_t^i)}, 1-\varepsilon, 1+\varepsilon\right) A_t^{\pi_\theta}\right)\right] \tag{7}$$

Intelligent Body i parameterizes the Critic network with a value function of $V_{\psi}(s_i^i)$. Network parameters θ and ψ are shared between Critic and Actor, respectively. For Intelligent Body i, its dominance is estimated in the following equation:

$$A_t^i = \sum_{l=0}^{h} \gamma^l \delta_{t+l}^i \tag{8}$$

where δ_t is the time-differential error of time step t, and the joint reward $r_t(s_t,a_t)$ is used to approximate the reward $r_t(o_t^i,a_t^i)$ of a single intelligent body as follows:

$$\delta_t^i = r_t(s_t^i,a_t^i) + \gamma V_{\psi}(s_{t+1}^i) - V_{\psi}(s_t^i) \tag{9}$$

In addition to cropping the strategy objective function, the value objective function is also cropped as a way of limiting the update of the Critic function to less than ε for each intelligence i:

$$\begin{aligned} J^i(\psi) = {} & \mathrm{E}_{s_i^i}[\min\{(V_{\psi}(s_t^i) - \hat{V}_t^i)^2, \\ & (V_{\psi_{old}}(s_t^i) + clip(V_{\psi}(s_t^i) - V_{\psi_{old}}(s_t^i), -\varepsilon, +\varepsilon) - \hat{V}_t^i)^2\}] \end{aligned} \tag{10}$$

where ψ_{old} is the old parameter before updating, and $\hat{V}_i^i = A_i^i + V_{\psi}(s_i^i)$. Limiting the update of the objective value function to the trust region by cropping helps to avoid overfitting to the latest batch of data.

Therefore, for each intelligence, the expression of the objective function for overall learning is:

$$J(\theta,\psi) = \sum_{i=1}^{n} J^i(\theta) + J^i(\psi) \tag{11}$$

III. C. 2) Improved MAPPO algorithm based on noise assistance

The Multi-Intelligent Body PPO (MAPPO) algorithm is an extension of the PPO algorithm for multi-intelligent body systems and an AC-like algorithm based on the CTED framework. Compared with IPPO, it requires a global value function to make each intelligent body cooperate with each other. In Actor network intelligent body i selects action a^i based on its own current local observation o^i through policy π_θ^i. In Critic network, using joint observation $(o^1, o^2, ..., o^n)$ and joint action $(a^1, a^2, ..., a^n)$ as inputs, the estimated value realizes the evaluation of the action and feeds back to the Actor network to influence the selection of the next action. So the objective function of Actor in MAPPO algorithm is:

$$J^i(\theta) = E_t\left[\min\left(\frac{\pi_\theta^i(a_t^i \mid o_t^i)}{\pi_{\theta_{sid}}^i(a_t^i \mid o_t^i)} A_t^{\pi_\theta}, clip\left(\frac{\pi_\theta^i(a_t^i \mid o_t^i)}{\pi_{\theta_{sid}}^i(a_t^i \mid o_t^i)}, 1-\varepsilon, 1+\varepsilon\right) A_t^{\pi_\theta}\right)\right] \tag{12}$$

Where, θ is the parameter of the strategy network and θ_{old} is the parameter of the previous time of the strategy network, so the loss of the Critic network which is also the objective function is:

$$J^i(\psi) = E[(V_\psi(o^1, o^2, ..., o^n) - r_t^i)^2] \tag{13}$$

where ψ is a parameter of the Critic value network and r_i^i is the reward value that has been estimated by generalized dominance.

Strategy overfitting in multi-intelligence cooperation can be solved by explicit credit allocation, i.e., the centralized dominance value can be decomposed to individual intelligences i with the mathematical expression $A(s, \{a_i^i\}_{i=1}^n) = \sum_i^n A^i(s, a^i)$. where s is the joint state and a^i is the action of intelligence i. By doing so, the shared dominance value will not affect unrelated intelligences. However, decomposing the correct dominance value A^i in a multi-intelligent body system is generally not easy.

Since the sampled dominance values are usually biased, these dominance values can be smoothed by noise to prevent overfitting of the multi-intelligent body strategy caused by the bias of the sampled dominance values and the non-smoothness of the environment, similar to label smoothing in image classification. In this section, a method using value noise to assist in policy regularization to improve the performance of the algorithm is proposed. For noise-assisted MAPPO, Gaussian noise is sampled for each intelligent body i, i.e:

$$x^i \sim N(0,1), \forall i \in n \tag{14}$$

where n is the number of intelligences. Next interfere with the dominant values by mixing the dominant values A^b with noise through noise weights β, where b is the small batch of samples. The multi-intelligent body strategy is trained by utilizing these noise dominant values. I.e:

$$A_b^i = (1-\beta) \cdot A^b + \beta \cdot x^i, \forall i \in n, b \in B \tag{15}$$

Randomly sample a Gaussian noise vector $\bar{x}^i \sim N(0, \sigma^2)$ for each intelligence i where σ^2 is the variance, which can be viewed as the noise intensity. Next the noise $\vec{x}^i$ is connected to the global state s. The spliced features are then fed into a centralized value network that generates noise values υ^i for each intelligent body i. i.e:

$$\upsilon^i = V(concat(s, \vec{x}^i)), \forall i \in n \tag{16}$$

Random noise $\bar{x}^i$ disrupts the network of centralized values and propagates to dominant values $A^i = r + \gamma\upsilon^i(s_t) - \upsilon^i(s_{t+1})$, interfering with the dominant values. The assisting noise prevents the bias of sampled dominance values and the non-smoothness of the environment from leading to overfitting of the multi-intelligencer strategy.

Finally, the noise-assisted MAPPO algorithm is proposed by combining the noise-dominant values and noise-valued functions with MAPPO.

The structure of the noise-assisted MAPPO-based algorithm is shown in Fig. 1.

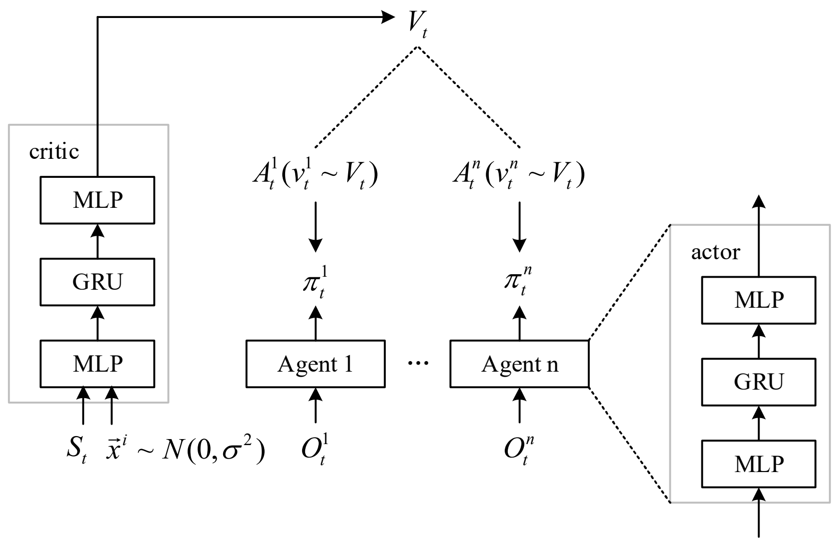

Figure 1: Structure diagram of MAPPO Algorithm Based on Noise Assistance

where the objective function of the Actor policy network is:

$$J_t(\theta) = \frac{1}{n}\sum_{i=1}^{n} \min\left(\frac{\pi_\theta^i(a_t^i \mid o_t^i)}{\pi_{\theta_{sid}}^i(a_t^i \mid o_t^i)} \hat{A}_b^i, clip\left(\frac{\pi_\theta^i(a_t^i \mid o_t^i)}{\pi_{\theta_{sid}}^i(a_t^i \mid o_t^i)}, 1-\varepsilon, 1+\varepsilon \right) \hat{A}_b^i \right) \tag{17}$$

The objective function of the Critic value network is:

$$J(\psi) = \frac{1}{n}\sum_{i=1}^{n}(\upsilon^i(\psi) - R^i)^2 \tag{18}$$

IV. Feasibility Analysis of Intelligent Dynamic Design for Cheerleading in Colleges and Universities

IV. A. Deep Reinforcement Learning-based Multi-Intelligent Body Path Planning

IV. A. 1) Experimental environment setup

The experimental hardware environment in this chapter is Intel Core i7-10700K CPU and NVIDIA GeForce RTX 3090 GPU.

A multi-intelligent body path planning simulation training environment was constructed based on the OpenAI platform. The simulation environment was a square 2D plane with a side length of 10m, and there were three groups of intelligent bodies and target locations in the environment. The radius and mass of each smart body were set to 0.3m and 2kg, the maximum speed was limited to 0.90m/s, the radius of the target position was 0.08m, and the radius of the obstacles in the environment was set to 0.5m. At the beginning of the training, all the smart bodies, the target position and the obstacles were randomly generated in the environment.

IV. A. 2) Training parameter settings

In this experiment, the MAPPO algorithm, the MADDPG algorithm, and the MAPPO algorithm, which are improved based on noise assistance, are used for training. All three algorithms were set with the same parameters, ReLU was used for the activation function, and the optimizer was Adam. The maximum number of training rounds was 10^5, the maximum number of time steps per round was 200, and the learning rate was set to 0.003. The network parameters were updated every 50 steps, the discount factor γ was 0.90, and the replay buffer size was 120, the training batch size is 512. parameters α and β are set to 0.3 and 12, respectively, and the potential field thresholds d_o and d_u are both set to 0.3.

IV. A. 3) Experimental results and analysis

Combined with the actual research needs of this paper (college cheerleading), dynamic obstacle experiments are mainly conducted here.

In order to verify the effectiveness of this paper's algorithm in accomplishing the multi-intelligent body path planning task in different scenarios, this paper conducts experiments in the case of dynamic obstacles. Meanwhile, two indexes, intelligent body collision rate and goal arrival rate, are defined to evaluate the performance of this paper's algorithm with the baseline algorithm. The collision rate includes the collision rate between intelligent bodies (CBRS) and the collision rate between intelligent bodies and obstacles (CBRO), while the target arrival rate (TAR) is expressed as the success rate of intelligent body path planning in each round.

In the dynamic obstacle experiments, the obstacles in the environment exist in a randomized moving manner and their moving speed ranges between 0 and 0.3 m/s. The complexity of this dynamic environment makes it more challenging for the intelligences to accomplish the path planning task.

The collision rate (CBRS) between intelligences in the dynamic experiment is shown in Fig. 2. The CBRS values of the three algorithms in the figure are controlled between 0 and 5. The MADDPG algorithm in the intervals of 2.0×10^4 to 4.0×10^4, 7.0×10^4 to 8.0×10^4 Large fluctuations occur and the CBRS is unstable. The improved MAPPO algorithm based on noise assistance consistently controls the CBRS around the value 1 throughout the training interval.

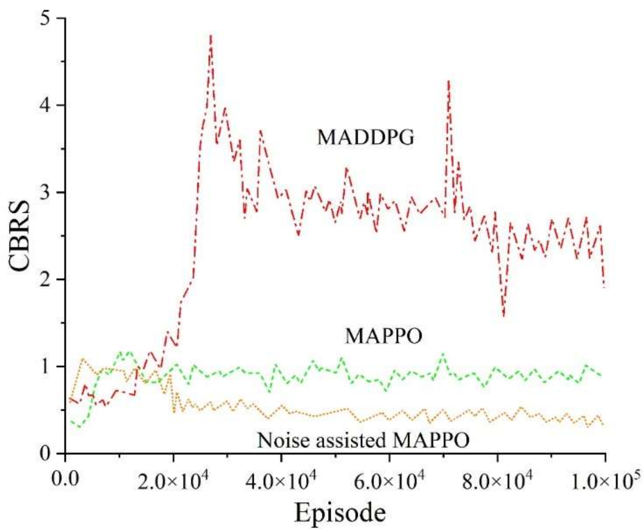

Figure 2: The collision rate between intelligent bodies in dynamic experiments

The collision rate (CBRO) between intelligences and obstacles is shown in Fig. 3. The MADDPG algorithm shows a large increase in the collision rate between intelligences and obstacles after the number of training enters into 2.0×10^4. The CBRO>6.

The CBRO values of MAPPO algorithm, improved MAPPO algorithm based on noise assistance are in the range of 1.0 to 2.0 and 0.5 to 2.0 respectively. And the CBRO value of improved MAPPO algorithm based on noise assistance is smaller.

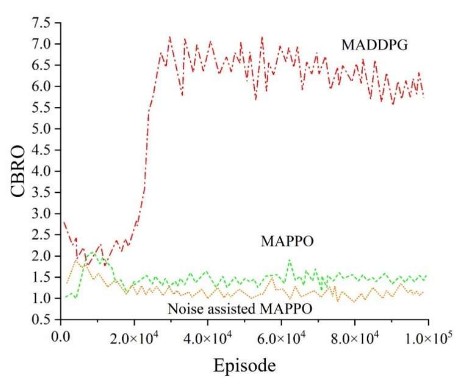

Figure 3: The collision rate between the intelligent body and the obstacle

The target arrival rate (TAR) is shown in Fig. 4. The improved MAPPO algorithm based on noise assistance reaches the maximum value of TAR at the early stage of training, and the TAR value is superior to other algorithms. This further indicates that the MAPPO algorithm introducing noise assistance in complex dynamic environments has superior obstacle avoidance performance.

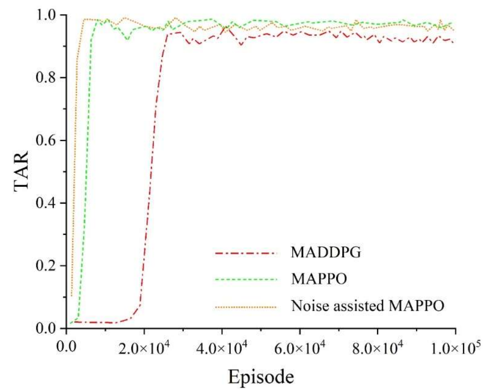

Figure 4: Target arrival rate

IV. B. Effect of Intelligent Dynamic Design of Cheerleading in Colleges and Universities

IV. B. 1) Purpose of the experiment

This paper takes the design and application of intelligent dynamic route for teaching flower ball cheerleading drill in colleges and universities as the object of research.

The sophomore students of two classes of preschool education majors in the preschool 3 department of a city's teacher training college have all studied one semester of mass aerobics and one semester of line dance in their freshman year, and they are more familiar with the traditional classroom of gymnastics and dance. With the help of the learning platform, we constructed the online resource library and classes for this course, formulated the teaching plan and teaching arrangement according to the pre-course learning survey, and tested the feasibility of multi-intelligence body reinforcement learning applied to the teaching of flower ball cheerleading in colleges and universities, and explored the differences between the traditional classroom and the intelligent classroom through the application experiment of the intelligent and dynamic route design for cheerleading teaching.

IV. B. 2) Experimental Objects

Subjects: 102 sophomore students in two classes majoring in preschool education in the preschool 3 department of a city teacher training college, in this paper, class 2024 is used as an experimental class and class 2023 as a control class.

In the experimental class, there were 8 boys and 42 girls, totaling 50 students, and in the control class, there were 7 boys and 45 girls, totaling 52 students. Separately, the class was randomly divided into four groups within the class, and the number of people in each group in the experimental class was 12, 13, 12, and 13, respectively. The number of students in each group in the control class was 13 to facilitate teaching arrangements.

IV. B. 3) Experimental time

After 15 weeks totaling 30 hours (September 2024 to January 2025), flower ball cheerleading theory was taught twice for a total of 4 hours (in the 1st and 8th class, respectively), practice was taught 12 times for a total of 24 hours, and the final examination was held once for a total of 2 hours.

IV. B. 4) Application effects

In order to compare and analyze the teaching effect of the application of intelligent dynamic path design and traditional class teaching of college flower ball cheerleading, the experimental class was selected as the class that used the intelligent classroom, and the control class was the class that did not use the intelligent classroom.

The teaching effect of the application of intelligent dynamic path design was investigated by comparing and analyzing the results of students' technical level test before and after the experiment. The technical level test of flower ball cheerleading adopts the principle of separation of teaching and examination, and the technical level test results of flower ball cheerleading in the experimental class and the control class before and after the experiment are scored by professional teachers with the qualification of cheerleading referee according to the “Scoring Standard for Technical Level Test of Flower Ball Cheerleading”.

The results of the paired t-test analysis of the technical level scores of the students in the experimental class before and after the experiment are shown in Table 1, which contains four aspects, i.e., movement standardization, emotional expression, formation transformation, and the overall presentation of cheerleading.

As can be seen from the table: there are a total of four groups of paired data, of which four groups of paired data will show differences.

Specific analysis can be seen: the experimental class students' movement technology, emotional expression, formation transformation and overall presentation level between the pre-test and post-test shows a statistically significant difference, p-value of 0.001. Summarize can be seen that the experimental class students' technical level has improved after the experiment.

Table 1: Test analysis results of the test of the test group

Item name		Group (mean ± standard deviation)		Difference value	t	p
		Pre-experiment	After experiment	Pre-experiment-after experiment		
Action	Premeasurement& posttest	77.85±5.19	86.24±3.47	-8.39	-7.223	0.001**
Emotional expression	Premeasurement& posttest	73.94±6.78	89.75±2.15	-15.81	-8.119	0.001**
Formation	Premeasurement& posttest	70.89±5.52	85.61±3.07	-14.72	-7.054	0.001**
Overall rendering	Premeasurement& posttest	74.23±6.12	87.20±3.59	-12.97	-8.721	0.001**

After the experiment, the experimental class and the control class were subjected to the flower ball cheerleading level test and the final test, and the experimental class and the control class were given the post-experimental technical level test scores and the final test score scores.

The analysis of the cheerleading level scores of the experimental class and the control class after the experiment is shown in Table 2, from which it can be seen that: different subgroups of samples show statistically significant differences for the technical level post-test and final test, which means that different subgroups of samples are different for the technical level post-test and the final test.

Specific analysis shows that the subgroups show statistically significant differences for the technical proficiency posttest, as well as specific comparison of the differences shows that the mean of the technical proficiency posttest is significantly higher in the experimental class than in the control class. The groups showed statistically significant differences for the final test, as well as specific comparative differences that showed that the mean of the experimental class was significantly higher than that of the control class.

To summarize, the experimental and control classes showed statistically significant differences for both the technical level post-test and the final test after the experiment, and the experimental class was better than the control class for both the technical level post-test and the final test.

Table 2: The experimental class and the cross-verse experiment were analyzed

Item name		Group (mean ± standard deviation)		t	p
		Laboratory class	Cross-reference class		
After experiment	Action	86.24±3.47	78.23±6.49	4.125	0.001**
	Emotional expression	89.75±2.15	80.95±4.23	5.208	0.001**
	Formation	85.61±3.07	77.03±5.06	4.136	0.003**
	Overall rendering	87.20±3.59	80.21±4.94	3.279	0.001**
Final test	Action	83.15±4.17	74.85±3.49	4.014	0.002**
	Emotional expression	80.25±5.98	75.87±4.35	5.228	0.001*
	Formation	82.57±6.06	73.52±5.64	3.787	0.005**
	Overall rendering	84.23±5.32	76.87±4.22	5.009	0.007**

V. Conclusion

The multi-intelligent dynamic design method for college cheerleading based on the deep reinforcement learning shortest path algorithm has achieved remarkable results in theoretical innovation and practical application. Algorithm performance tests show that the improved MAPPO algorithm demonstrates excellent stability in dynamic environments, with the inter-intelligent body collision rate stably controlled near 1 and the collision rate with obstacles maintained in the range of 0.5-2.0, which is significantly better than the volatility performance of the traditional MADDPG algorithm. Teaching application experiments confirmed the practical value of the method, and the students in the experimental class realized significant improvement in all dimensions of technical level, with 14.72 points of improvement in formation conversion ability, 12.97 points of improvement in overall presentation level, and the final test score of 84.23 points significantly exceeded the 76.87 points of the control class. Statistical analysis showed that the experimental class and the control class showed statistically significant differences in technical level and final test, with a P-value of 0.001, which fully verified the teaching effect of the intelligent dynamic design method. This study breaks through the technical bottleneck of traditional cheerleading teaching and opens up a new path for the application of multi-intelligent body cooperative control theory in the field of physical education. In the future, we can further explore the application potential of the algorithm in larger-scale group exercise teaching, improve the construction of intelligent physical education teaching system, and promote the digital transformation and upgrading of physical education courses in higher education.

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