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Shortest Path Algorithm Based Cheerleading Formation Design and Movement Coordination Optimization in Colleges and Universities under Multi-Intelligent Body Environment

Lisha Zhang[1], Yan Liu[2,✉]

[1] *Hunan Mass Media Vocational and Technical College, Changsha, Hunan, 410000, China*
[2] *Changsha Preschool Education College, Changsha, Hunan, 410000, China*

ABSTRACT
Cheerleading events are flourishing in China, the level of competition is rising, the number of competition groups and programs is increasing, the competition is becoming more and more intense, and the innovative research on formation design is an inevitable demand for the development trend of cheerleading. The study designed a multi-objective path planning model based on the intensity of willingness and consultation strategy, so that college cheerleading can avoid conflicts and reach the goal point of cheerleaders in the complex environment. Then an improved multiobjective particle swarm algorithm (MOPSO-CA) based on metacellular automata is proposed and applied to college cheerleading formations to realize the design of college cheerleading formations. The simulation results show that the MOPSO-CA algorithm can re-select the optimal movement direction angle according to the real-time positions of the moving obstacles and moving targets, which illustrates the effectiveness of the algorithm. Secondly the feasibility of the formation design conditions are suggested as: keeping the originality of the movement, the use of the moving route of the formation and the space of the venue, and the type of formation change.

Keywords: multi-objective paths, metric automata, particle swarm algorithm, formation design

1. Introduction

Cheerleading originated in the United States, at first it was a kind of cheering sport for the competition teammates, since the emergence of cheerleading team in colleges and universities, it has gradually been valued and favored by people, and has developed rapidly in college campuses. With the improvement of people's living standards, cheerleading's unique fitness, bodybuilding, entertainment

✉ Corresponding author.
E-mail address: liuyan16673888805@163.com (Y. Liu).
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and other values have gradually come to the forefront, and its unique beauty and value have attracted the widespread attention of Chinese college students, who are actively involved in enjoying the fun and sense of achievement that cheerleading brings to them [1-3].

With the vigorous development of cheerleading events in China, the increasing level of competitions, and the increasing number of competition groups and programs, the competition in the selection and creation of cheerleading formations has become more and more intense [4]. As the carrier of highlighting set movements and the basis of influencing set scoring, the formation design has become the highlight and innovation point of set competition, and the innovative research of formation design is the inevitable demand of the development trend of cheerleading [5-7]. Novel and unique formation changes can get higher evaluation and occupy a certain advantage in the competition, and formation changes are also the key to perfect cheerleading sets and highlight the visual effect, in addition, the visual effect produced by the novelty and uniqueness of flower ball cheerleading formation changes is more prominent compared with that of other dance cheerleading [8-11]. Therefore, the study of college cheerleading formation design and sports coordination optimization can provide reasonable and scientific guidance for the creation of coaches and athletes, and on the basis of enriching the elements of cheerleading art creation, it can bring practical guidance for coaches to improve the level of leading the team and the ability of creation.

The article firstly designed a multi-objective path planning model, then modeled the environment in terms of the cell space, introduced the group adaptive mechanism, searched for the target point through the particle fitness and the environment marking information, and proposed an improved multi-objective particle swarm algorithm based on the cellular automaton to realize the cheerleading team formation in colleges and universities. The algorithm is validated and compared with simulation and MobileSim experiments for the problems of obstacle avoidance of cheerleaders as well as formation and maintenance of cheerleading formations.

2. Optimization of cheerleading formation movement coordination in colleges and universities

2.1. Multi-objective path planning model for high school cheerleading formation

In order to solve the problems of conflict and deadlock of college cheerleading teams in a multi-intelligent body environment, many scholars have carried out a lot of work on collision detection. The basic methods for solving such problems:

1) Organizational coordination. Organizational coordination refers to setting up an organizational structure that implies the attributes of cheerleaders such as competence, responsibility, control flow of the system and mutual communication with other cheerleaders. It is the simplest method of coordination, where a framework is constructed to coordinate the relationships between cheerleaders based on their roles, communication paths, and affiliations.

2) Multi-Intelligence Planning and Coordination. Multi-intelligence planning and coordination means that in order for cheerleaders to reach their goals safely and smoothly, a plan is developed based on the future actions of each cheerleader and the coordination required to accomplish their respective tasks. The program is refined through repetitive planning. There are two types of multi-intelligence planning: centralized multi-intelligence planning and distributed multi-intelligence planning.

3) Consultation. Consultation refers to the process of mutual communication and exchange in order for a group of intelligences to reach a mutually acceptable solution. It is the most common type of coordination mechanism, and all of the previous coordination methods have some form of consultation running through them. Depending on the strategies and techniques used in the consultative approach, different coordination strategies and methods are developed. These strategies

and techniques include optimization methods, methods of logic, model-based reasoning, and theories related to cognitive science. For cheerleading teams, all of these strategies and methods are worth exploring and delving into.

Here the behaviors of college cheerleaders are classified into three kinds: running to the goal, collision avoidance and negotiation behavior. Based on the behavior-based approach, the strength of willingness is introduced to solve the comprehensive problem of multiple behaviors of cheerleaders.

2.1.1. Basic behavioral design

1) Running Toward Target Behavior

$$V_{gaal} = \frac{v_{\max}}{\sqrt{\left(x_g - x_c\right)^2 + \left(y_g - y_c\right)^2}} \begin{bmatrix} x_g - x_c \\ y_g - y_c \end{bmatrix} \tag{1}$$

where $v_{\max}$ is the maximum velocity value that the cheerleader has, and V_{gaal} is a velocity vector.

2) Collision avoidance behavior. The collision avoidance planning behavior is mainly to avoid the collision between cheerleaders and static obstacles.

$$V_{collision} = v \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_d \\ y_d \end{bmatrix} \tag{2}$$

where, $\left[x_d, y_d\right]^T$ for the current direction of the cheerleader; θ for the angle of rotation to the cheerleader's own center point for the axis, clockwise rotation is negative, counterclockwise rotation is positive; v for the cheerleader's physical system of the allowable speed value, the value can not be greater than the cheerleader's perception in the direction of the $\left[x_d, y_d\right]^T$ angle of rotation θ detected in the direction of the distance and the quotient of the unit time; $V_{collision}$ velocity vector.

2.1.2. Intensity of Willingness and Consultation Strategies. Suppose that the sensing information detected by a particular cheerleader is represented by a regular set, viz:

$$\Omega = \left\{\Omega_1, \Omega_2, K, \Omega_n\right\} \tag{3}$$

where Ω denotes the total set; $\Omega_i (1 \le i \le n)$ denotes the sub-set and satisfies $\Omega = \Omega_1 Y \Omega_2 Y \Lambda Y \Omega_n$, $\Omega_i I \Omega_j = \Phi (i \ne j)$.

Based on the definition of cheerleader behavior that is closely related to the sensor information can be $\Omega = \Omega_1 Y \Omega_2 Y \Lambda Y \Omega_n$, $\Omega_i I \Omega_j = \Phi (i \ne j)$ obtained corresponding to the behavioral decisions of cheerleaders with different perceptual information, i.e:

$$H = \left\{H_1, H_2, \Lambda, H_n\right\} \tag{4}$$

where, H is the set of behavioral decisions corresponding to the total set of sensed information Ω; H_i is the subset of behavioral decisions corresponding to the subset of sensed information Ω_i.

Determine the meaning of cheerleaders to take a certain behavioral decision, the most desirable behavioral decision related to the goal g^* for the benchmark of its determination of the size, that is:

$$i = f\left(h - g^*\right) \tag{5}$$

where i is the willingness value of cheerleaders when taking behavioral decision h; $f(\cdot)$ is the willingness function of cheerleaders when taking behavioral decision h. When $h = g^*$, the intensity of willingness i is the largest value. When $h \neq g^*$, that is, behavioral decision h deviates further from the ideal behavioral decision g^*, the value of willingness strength i is smaller.

For the behavioral decision subset H_i above the sensor information subset Ω_i the willingness strength value is:

$$I_i = \sum_{H_i} f\left(h - g^*\right) \tag{6}$$

where $h \in H_i$, I_i are the willingness strengths of the behavioral decision subset H_i.

2.1.3. Implementation of Cheerleading Formation Coordination Based on Willingness Intensity:

1) Cheerleading Formation Structure. In order to ensure that cheerleaders avoid collisions, run to the goal and the collaboration between cheerleaders three goals are coordinated to ensure a reasonable synthesis of the three behaviors, multiple behavioral synthesis decision-making is designed to synthesize these three types of behavior, and to give cheerleaders the desired speed. When the cheerleaders have successfully negotiated, the desired speed will be output for execution.

2) Synthesis of collision avoidance behavior and run-to-target behavior. The collision avoidance behavior and the run-to-target behavior have both commonalities and differences, so the differences between the two are weighed to ensure that the two behaviors can be satisfied to a certain extent. Because the collision avoidance behavior generated by the sensing information is a collection of velocity vectors, it is divided into a series of sub-collections based on the presence or absence of obstacles in the sensing area ahead of the velocity direction. The unit direction vector of the velocity vectors of these subcollections is the angle of rotation required to rotate the unit direction vector referred to by the cheerleader's current direction of movement to this direction of velocity, which is negative for clockwise rotation and positive for counterclockwise rotation.

2.2. Shortest path algorithm based on MOPSO-CA algorithm

2.2.1. MOPSO-CA algorithm idea. The group motion simulation is divided into two parts: scene modeling and path planning. In the scene modeling part, the idea of metacellular automata is used to preprocess the scene, divide the scene into metacellular spaces, and represent the scene information with the state of each metacellular space, which reduces the difficulty of searching the environment and lays the foundation for the path planning process. In the path planning part, the improved multi-objective particle swarm algorithm is used for path search.

2.2.2. Modeling the Vertical Cellular Automata Environment. The Moore-type two-dimensional quadratic grid tuple automaton shown in Fig. 1 is utilized for environment region delineation. The geometric environment space is divided into a tuple space, where tuples mark the state of each location in the environment. The black tuple denotes the central tuple and the diagonal tuples denote the neighbors of the central tuple. A particle can next move in the direction of its 8 neighboring tuple spaces, and the optional direction of movement depends on the individual's next direction of movement and the current state in which its neighboring tuples are located.

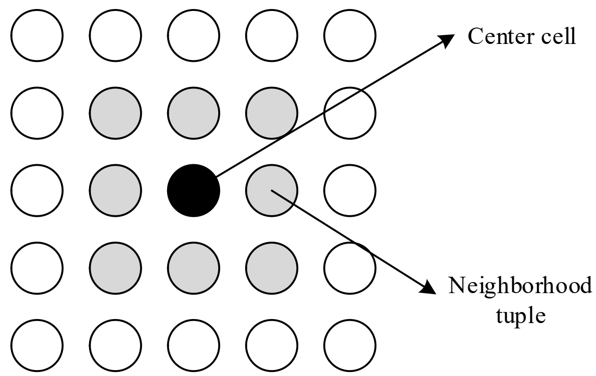


Fig. 1. Moore type two-dimensional square grid cell automata

To use the metacellular space to represent the environmental information, the precision of the metacellular space needs to be determined first. If the precision of the metacellular space is too coarse, the final performance will be distorted. If the precision is too fine, the computational complexity will be greatly increased, which will reduce the operational efficiency and affect the performance effect. When the MOPSO-CA algorithm is applied to the group exercise formation transformation problem, it should take the actual problem into full consideration, and based on the number of people involved in the performance and the size of the target formation, the performer's stations are determined, and each station is treated as a metacellular space unit.

2.2.3. MOPSO-CA algorithm. PSO algorithm is a kind of group intelligence algorithm simulating biological behavior, individuals can adjust the next step according to the current state, so that the group shows a certain intelligent type, with the advantages of simple arithmetic and few parameter settings [12]. In order to balance the global search ability and local improvement ability of PSO algorithm, the MOPSO-CA algorithm introduces group self-adaptation mechanism, adopts the dynamic inertia weight coefficient formula to update the value of weight w; and adopts asynchronous change of the learning factor, so that in the initial stage of the search for the optimal, the particles have a larger self-learning ability and a smaller social learning ability, to strengthen the search for global areas, and in the later stage of the search for the optimal, gradually In the later stage of the optimization search, the self-learning capacity is reduced and the social learning capacity is increased, which helps to search more finely until converging to the global optimal solution.

2.3. Based on MOPSO-CA college cheerleading formation solving

2.3.1. Algorithm execution process:

1) Particle initialization. Random initialization of particle position, velocity and other parameters.

2) Static environment preprocessing. Use Moore-type two-dimensional quadratic grid cellular automata to divide the environment space, and set ω weight according to the spatial state (FULL or NULL).

3) Dynamic path planning. The particle is paired with the target D^j, and the optimal solution is evaluated according to the optimization functions $F(x)$ and $G(x)$, and the pairing result is stored in PSOList.

4) Group behavior control. Adopting group adaptive mechanism to realize interaction with the environment and path correction to avoid collision.

5) Path adjustment. After reaching a certain number of iterations, re-execute the pairing and calculate the optimization function, if the new optimization function value is better than the result in PSOList, then execute the update and perform step (4) to achieve dynamic solution to the global optimum.

6) If the iteration conditions are satisfied, complete the path planning and output the global optimal solution and the particle optimal path in PSOList. Otherwise, return to step (3).

2.3.2. Initialization. Setting the population size to N, assume that in the m-dimensional search space, the position and velocity of the i rd particle are $X^i = (x_{i1}, x_{i2}, \cdots, x_{im})$ and $V^i = (v_{i1}, v_{i2}, \cdots, v_{im})$ respectively, and the target position of particle j is denoted as $D^j = (d_{j1}, d_{j2}, \cdots, d_{jm})$.

2.3.3. Dynamic path planning. The particle scans the target position in the environment sequentially, and calculates the current optimal target position of the particle based on Eq. (7) and Eq. (8) to get the pairing result.

$$mp_{ik} = \sqrt{\sum_{j=1}^{m} \left(x_{ij} - d_{kj}\right)^2} \tag{7}$$

$$p_i = \min\left(mp_{ik}\right) \tag{8}$$

where m denotes the dimension of the candidate solution. x_{ij} denotes the j th dimensional coordinate of particle i, d_{kj} denotes the j th dimensional coordinate of the k th target position; mp_{ik} denotes the distance between particle i and target k, and p_i is the smallest of k mp_{ik}, which denotes the optimal position obtained by the search of particle i.

The following rules need to be satisfied for a pairing to be “good”:

Rule 1 The path from the initial position to the target position of an individual is as short as possible.

Rule 2 Keep the relative positions of the individuals and do not change the overall layout significantly.

Rule 3: The total path of the whole group should be as short as possible.

According to these three points, the optimization function of the formation transformation problem, which is a multi-objective path optimization problem, can be expressed as follows:

$$F(x) = \sum_{j=1}^{N} p_j \tag{9}$$

$$G(x) = \sum g(A, B) \tag{10}$$

where $F(x)$ realizes the guarantees for Rule 1 and $\sum g(A, B)$ realizes the guarantees for Rule 2.

2.3.4. Group behavior control. After determining the target position, the adaptation function and the learning factor of asynchronous transformation shown in Eq. (5) guide the particle velocity update, predict the metacellular grid space that will be reached in the next unit of time, and dynamically adjust the particle motion to realize collision avoidance during the motion process, which enhances the simulation and realism of the algorithm.

$$f_{fit}(i) = \alpha \sqrt{\sum_{j=1}^{m} \left(x_{ij} - p_{ij}\right)^2} + \rho\omega \tag{11}$$

where α and β are the influence factors. ω is the weight of the metric space.

The particle velocity and displacement are updated with Eq. (12) and Eq. (13) during the particle motion:

$$\begin{aligned} v_{ij}(t+1) = {} & wv_{ij}(t) + c_1 r_1 \left(p_{ij} - x_{ij}(t)\right) \\ & + c_2 r_2 \left(p_{gj} - x_{ij}(t)\right) \end{aligned} \tag{12}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1), j = 1, 2, \cdots \tag{13}$$

where w is the inertia weight, c_1 and c_2 are the learning factors. The learning factors use the asynchronous update mechanism shown in Eqs. (14), (15):

$$c_1 = c_{1ini} - \left(c_{1ini} - c_{1ini}\right) / t_{\max} \times t \tag{14}$$

$$c_2 = c_{2ini} = \left(c_{2fin} - c_{2ini}\right) / t_{\max} \times t \tag{15}$$

where c_{1ini} and c_{2ini} represent the initial values of c_1 and c_2, respectively, and c_{1fin} and c_{2fin} represent the final values of the iteration. The learning factor varies with time, which is favorable for a strong global search capability in the early stage of optimization, and in the late stage of optimization, it gradually converges to the optimal solution.

The change process of inertia weight w is shown in equation (16):

$$w = \begin{cases} w_{\min} - \dfrac{\left(w_{\max} - w_{\min}\right) \times \left(f - f_{\min}\right)}{f_{av} - f_{\min}} f \le f_{av} \\ w_{\max} f > f_{av} \end{cases} \tag{16}$$

where f denotes the current fitness function value of the particle; f_{av} and $f_{\min}$ denote the average fitness value and the minimum fitness value of all current particles, respectively. The time-dependent inertia weights avoid falling into local optimality during the optimization search process.

2.3.5. High School Cheerleading Formation Transformation. In the process of college cheerleading sports, often a formation form can not make the whole system safely through the obstacles to reach the destination, so in the college cheerleading sports often formations change. For specific practical problems, according to the characteristics and requirements of the task, college cheerleading can form the following common formation patterns, as shown in Figure 2.

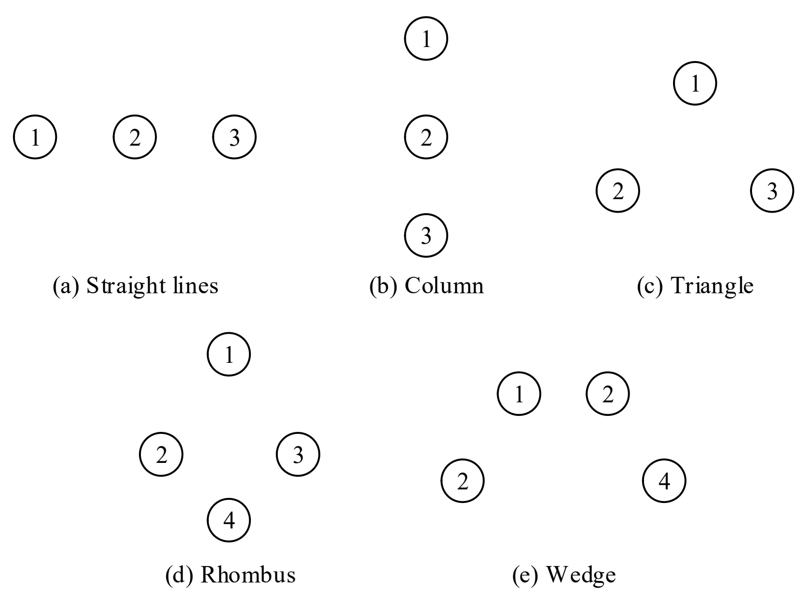


Fig. 2. A typical college cheerleading formation

According to the improved leader-follower method given in the previous section, when the leader receives the information iI from each follower, the leader makes a decision based on the actual situation: if the current formation is not suitable for the environment in which it is located, the leader will replan and determine a new formation, and then use communication means to notify other follower, each follower receives the notification and calculates its desired position by combining its own detected environment information, and then returns the information to the leader, who will rejudge whether the formation needs to be adjusted or not. When the leader's re-planned strategy still fails to satisfy the current environment, the leader will designate another cheerleader as the new leader, who will continue to lead the college cheerleading team to move forward to the goal.

3. Analysis and practice of cheerleading formations in colleges and universities

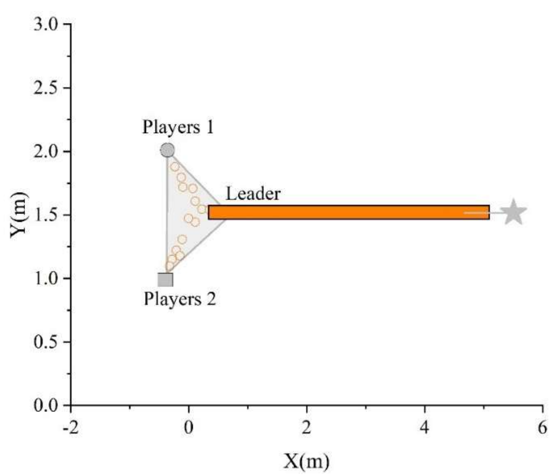
3.1. Matlab simulation experiment and algorithm comparison analysis

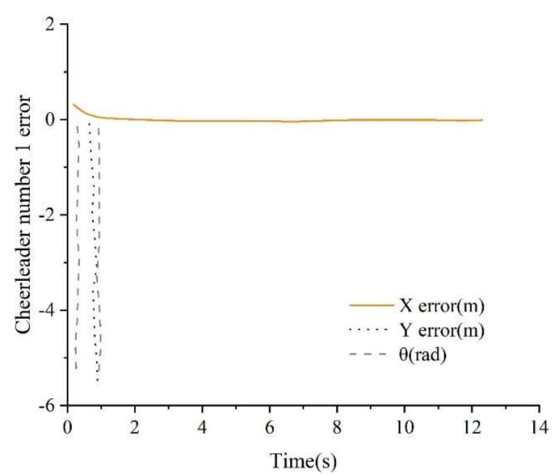
To validate the proposed algorithm, several sets of simulations were performed in Matlab. Each cheerleader is considered as a sphere and its direction of motion is any one of the directions between $[0, 2\pi]$. The linear velocity of the leader is fixed to $v_i = 0.1\mathrm{m/s}$. Some of the parameter values in this section are $V_{\max} = 0.5m/s$, $K_1 = 0.3s^{-1}$, $K_2 = 0.08s^{-1}$.

3.1.1. Cheerleading formation changes. Figure 3(a) shows the formation planning trajectory of the three cheerleaders in the formation system as they change from a triangular formation to a linear formation. The initial positions of the cheerleader, team member 1 and team member 2 are set to $(0.5m, 1.5m)$ and $((0.5-\sqrt{0.75})m, 2m), ((0.5-\sqrt{0.75})m, 1m)$, respectively, and the desired distances between the leader and cheerleaders 1 and 2 in the linear formation are $L_d = 0.4m$ and $L_d = 0.8m$, respectively, and the desired angle is $\varphi_d = 0$.

Figure 3(b)(c) shows the state error changes of the two cheerleaders during the formation transformation process, respectively. It can be seen from the figure that with the smooth transformation of the formation, the state error of the cheerleaders tends to zero quickly and efficiently, which indicates that the successful realization of the formation transformation - from the initial triangular formation to the desired linear formation - is achieved.

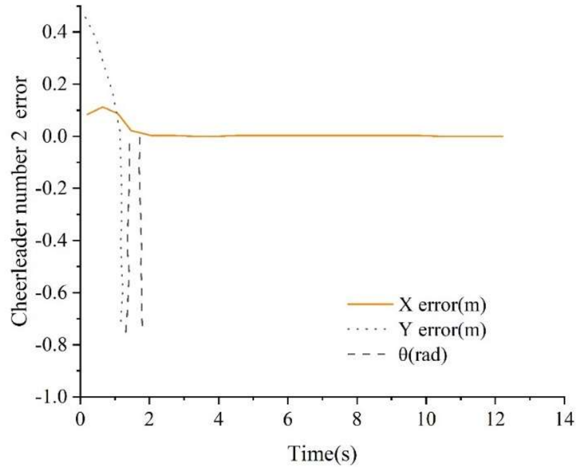
The algorithm proposed in this paper and the traditional algorithm are respectively used to realize the formation transformation when the above simulation environment is set up, and the error convergence time of the two following cheerleaders is compared, and the results are shown in Table 1. The results are shown in Table 1. It can be seen from the table that the state error convergence time of the formation transformation using the algorithm proposed in this paper is shorter than that of the traditional algorithm, which indicates that the algorithm proposed in this paper can ensure the fast and smooth transformation of the formation. The random cheerleaders are subject to the combined force from the leader, but because the distance between the cheerleaders and the leader is farther (farther than the distance between the cheerleaders and the leader), the gravitational force from the leader on the No. 2 player is smaller than that of the No. 1 player on the No. 1 player, so the state error convergence time of the No. 2 player is longer than that of the No. 1 player. After realizing the formation transformation, the state error convergence accuracy of the two cheerleaders can reach 10^{-5}m.





(a) The formation transformation trajectory

(b) State error of player 1



(c) State error of player 2

Fig. 3. The proposed algorithm is used for the simulation results of the formation transformation

Table 1. Comparison of state error convergence time by different algorithms

	State error convergence time of player No.1 (s)			State error convergence time of player No.2 (s)		
	x	y	θ	x	y	θ
This algorithm	1.8	1.5	1.7	2.1	1.9	1.9
Traditional algorithm	5.6	4.7	4.7	1.6	1.6	1.6

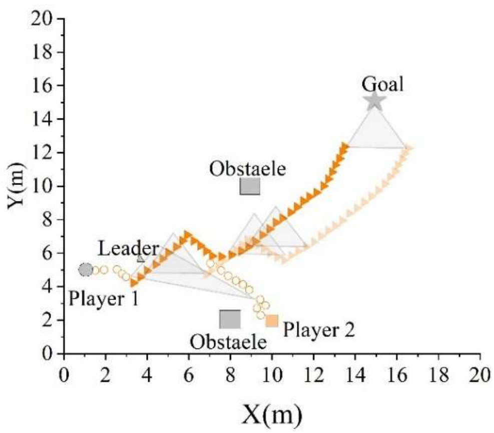
Using the algorithm proposed in this paper, college cheerleaders can quickly form the desired formation, and the state error accurately tends to zero, and the performance of the algorithm is better than the traditional algorithm.

3.1.2. Cheerleading formation obstacle avoidance. The simulation is used to verify that the algorithm proposed in this paper can not only successfully form the desired formation but also avoid obstacles, and the comparison with the traditional algorithm illustrates the superiority of the algorithm proposed in this section.

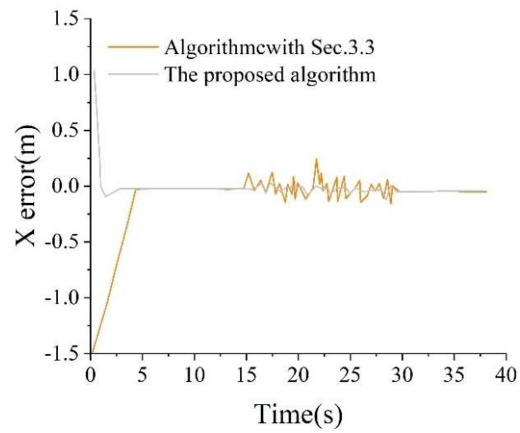
Some simulation results in the process of formation planning and obstacle avoidance are shown in Figure 4. The initial positions of the cheerleading leader, No. 1 cheerleader, and No. 2 cheerleader are (4m, 6m), (1m, 5m), (10m, 2m), the target position of the system is (15m, 15m), the obstacle position is (8m, 2m), (9m, 10m), and the obstacle size is 0.5m×0.5m. The expected formation is an equilateral triangle with an expected distance of $L_d = 3\text{m}$ between the leader and the cheerleader.

Fig. 4(a) shows the trajectory of formation obstacle avoidance, and the obstacles appear in the paths of the cheerleader and cheerleader #2. Fig. 4(b)-(e) shows the positional errors of the two cheerleaders in the x-direction when the algorithm of this paper and the traditional algorithm realize the formation planning and obstacle avoidance. From the figure, it can be seen that the No. 2 cheerleader can successfully avoid obstacles and form the desired formation, and the two cheerleaders can track the cheerleader at the desired distance and desired angle. Figure 4(f) shows the distance between the cheerleaders and the obstacles during the process, indicating that the cheerleaders can successfully avoid the obstacles encountered.

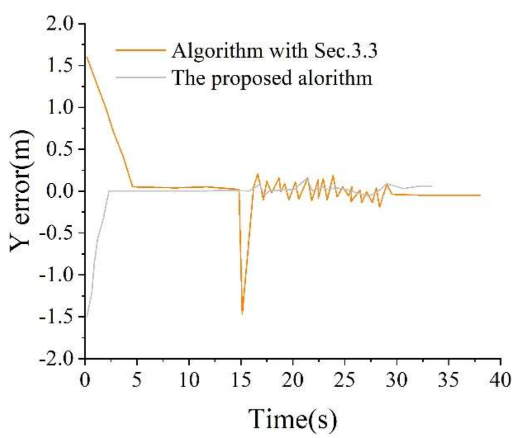
The results of the position error convergence time comparison when using the two algorithms to realize formation obstacle avoidance are shown in Table 2. From Fig. 4(b)-(e) and Table 2, it can be seen that in the process of accomplishing formation obstacle avoidance, the convergence time of the x-direction and direction position errors of the proposed algorithm in this section is much smaller than that of the x-direction and y-direction position errors of the traditional algorithm. When the traditional algorithm is used to realize the formation obstacle avoidance, the college cheerleaders need to change the formation from triangular to linear, so that obstacle avoidance can be realized in the narrow environment; however, when the cheerleading team encounters the obstacles, the position errors of the two cheerleaders can not be well converged to zero. The algorithm in this paper does not need to change the formation when the cheerleader encounters an obstacle, and can form and maintain the formation better. Using the algorithm in this paper, the No.2 cheerleader can quickly form a formation and avoid obstacles, and when the cheerleader encounters obstacles, the two cheerleaders can successfully maintain the formation.



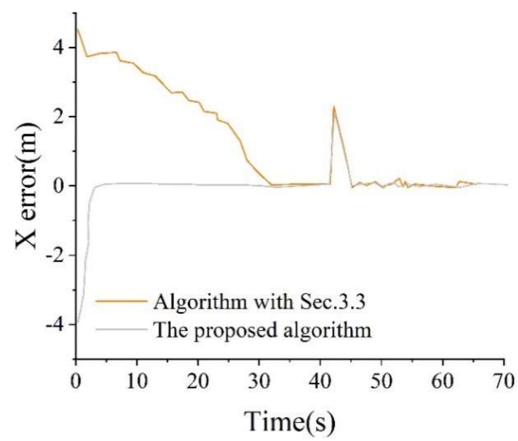
(a) Formation obstacle avoidance track



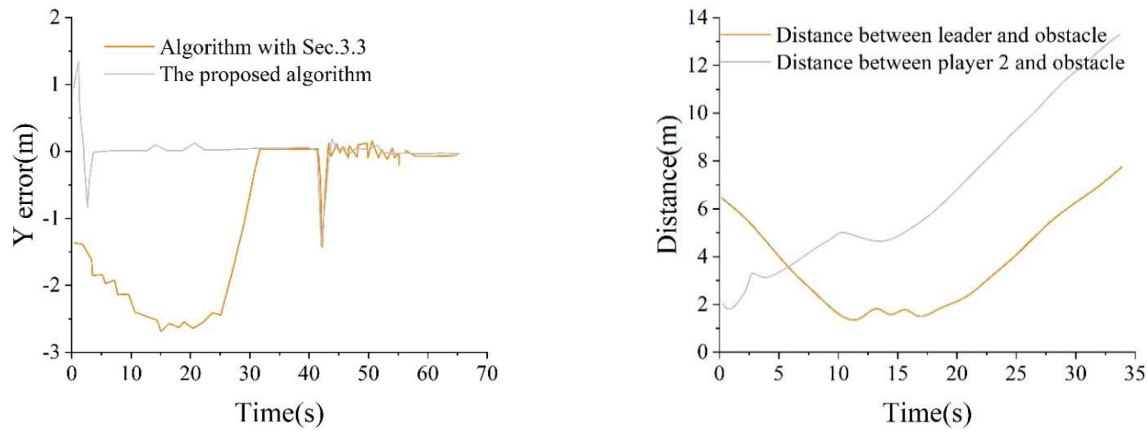
(b) Team 1 has an x direction error



(c) The y direction error of team 1



(d) The x direction error of team 1



(e) The y direction error of team 2

(f) Distance between players and obstacles

Fig. 4. Simulation results for formation obstacle avoidance are implemented using different algorithms

Table 2. The difference of position error convergence time is compared

	State error convergence time of player No.1 (s)		State error convergence time of player No.2 (s)	
	x	y	x	y
This algorithm	2.8	2.8	4.1	4.1
Traditional algorithm	4.7	4.7	33.2	33.2

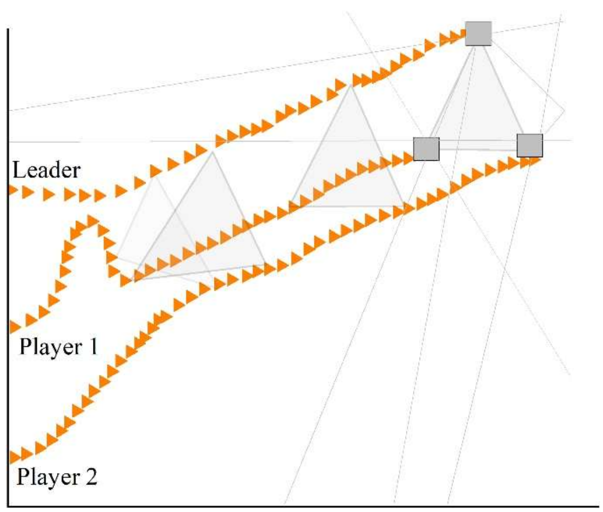
From the above analysis, it can be seen that using the algorithm proposed in this paper, the college cheerleaders can successfully avoid obstacles with the desired formation, and the cheerleaders can successfully avoid obstacles in the process of tracking the cheerleading leader.

3.2. MobileSim Experimental Verification

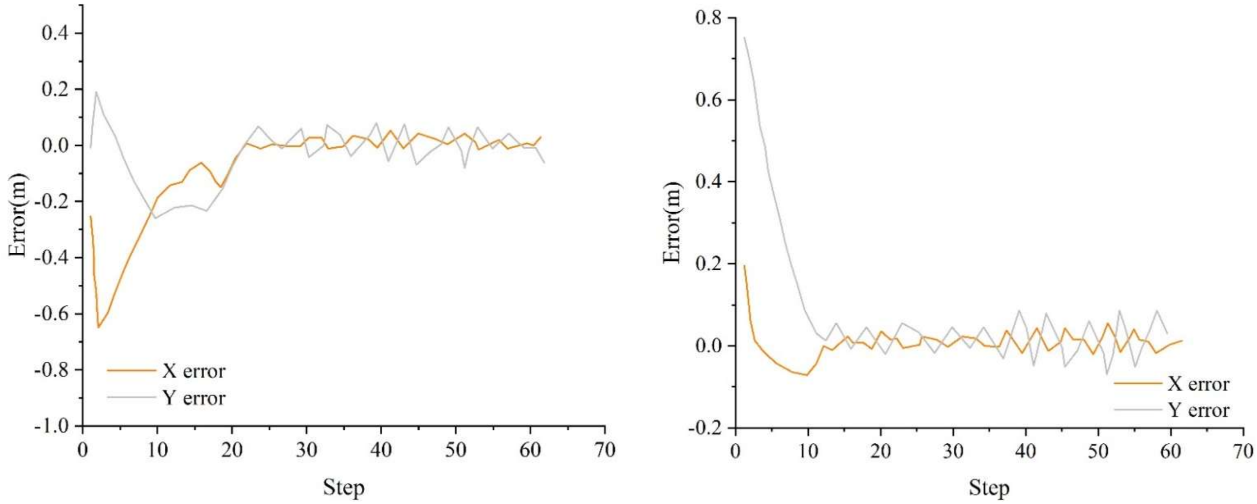
The algorithms presented in this section are verified on the MobileSim emulator, which provides a connectivity option that can be used in place of the AmigoBot. There are eight sonars on the AmigoBot in the emulator, which can be used for object detection and distance detection. The program implemented on the emulator has the same effect as the program executed on the real AmigoBot.

In the experiment, the initial positions of the three cheerleaders were set to (0m,0m), (0m,-1m), and (0m.-2m). The leader's linear velocity was set to v_i =0.15m/s and the maximum linear velocity of the cheerleaders was set to $V_{\max}$ =0.5m/s.

3.2.1. Cheerleading formation changes. This experiment is used to verify that the algorithm proposed in this paper can realize the smooth transformation between two team shapes in MobileSim simulator. The desired formation is an equilateral triangle, and the desired distance between the cheerleaders is L_d =1m Some experimental results of three cheerleaders transforming between the two formations are shown in Fig. 5, from which it can be seen that the cheerleaders can quickly track the cheerleading leader.



(a) Formation transformation plans the trajectory



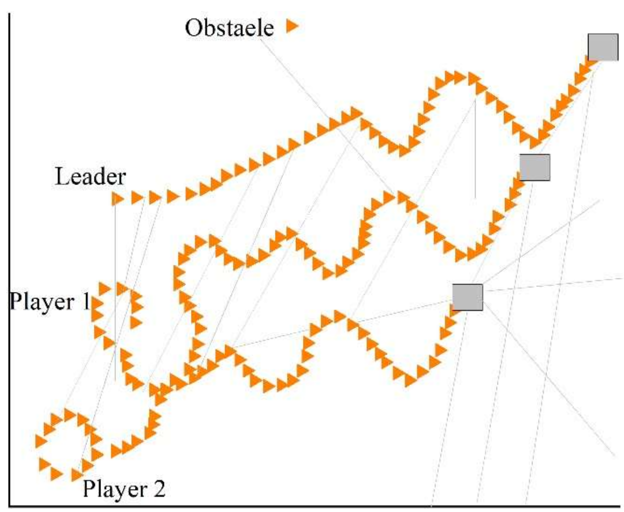
(b) Position error of player 1

(c) Position error of player 2

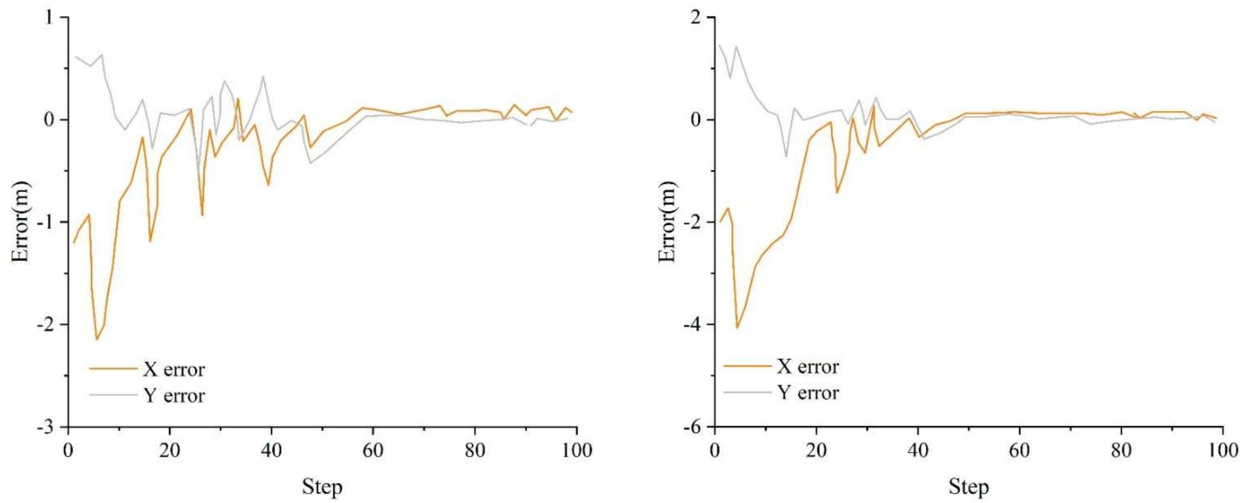
Fig. 5. The formation transformation was implemented on the mobilesim simulator

3.2.2. Cheerleading formation obstacle avoidance. The experiment verifies that the algorithm proposed in this section can form the desired formation and successfully avoid the obstacles in the desired formation in the MobileSim simulator. The location of the obstacle is set as (4m,2m), and the desired distance and angle between the cheerleaders are L_d =1.5m and $\varphi_d = \pi/3$, respectively.

Some experimental results of implementing formation obstacle avoidance on the MobileSim simulator are shown in Figure 6. From the figure, it can be seen that the position error of the cheerleaders converges to zero quickly and keeps the position error to zero during the obstacle avoidance process, which indicates that the college cheerleaders can form the desired formation successfully and avoid obstacles successfully with the desired formation.



(a) Formation transformation plans the trajectory



(b) Position error of player 1 (c) Position error of player 2

Fig. 6. The formation transformation was implemented on the mobilesim simulator

3.3. Empirical Analysis of Cheerleading Formation Change Designs

3.3.1. Cheerleading formation design. Cheerleading formations are roughly divided into four corners and five areas in the middle of the competition field, and meticulously divided into nine areas: front center, center, back center, left front, left back, left center, right center, right front and right back. In cheerleading formations, the visual effects of different formations are very different. The general formation is located in the center or in the middle of the front position is most likely to attract the referees and the audience, the visual effect expressed by the visual table is relatively prominent, and has a strong visual impact.

Formation combination of different forms is the composition of sets of formation changes in the characteristics of the basic elements, the number of different combinations of forms designed to make reasonable use of each area of the site, but also reflects the artistic and aesthetic value. For example: 16 people change the combination of formation diagram shown in Figure 7, the use of different combinations of the number of people in the form of different venues and different site location selection, and the formation of different types of formation pattern effect. (Orange in the figure represents the level)

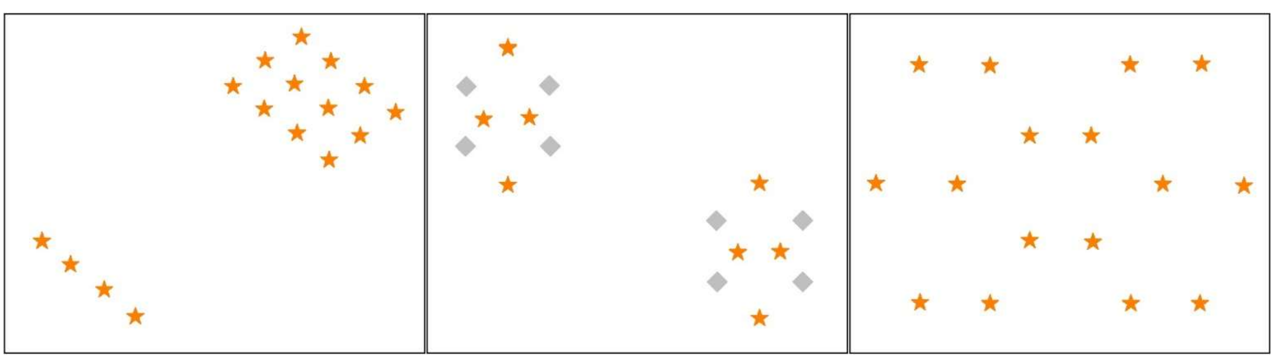


Fig. 7. Different number of people combination forms

3.3.2. Number of formation changes. The novelty, innovation and variety of changes in cheerleading formations are conducive to improving the ornamental properties of sets of movements. In the process of competition, it is mainly through the different combinations of athletes in the form of formation changes and movement, and on the basis of following the rules, make full use of the fixed and mobile formations to show the best visual effect of the sets of movements, fully demonstrate the unique charm of cheerleading formations, and give the referees and the audience a brand new visual experience, which is more conducive to improving the performance of the competition. The number of changes in the formation of set movements is shown in Table 3 (X1 is the fixed formation, X2 is the flowing formation, Y is the repeating formation, B is the ratio, C is the repeating formation, and T is the total number).

From the table, it can be clearly concluded that the 15 teams participating in the cheerleading competition have a minimum of 17 total formation changes, of which the higher the ranking of the participating teams in Group A, the more the total number of formation changes, the first place is as high as 30 times, and the average value of the seven teams is 21.1 times, and the total number of formation changes of the participating teams in Group B is not much different, the most is the second place reaches 20 times, and the average value of the 8 teams is as high as 25.5 times. Based on the total number of formation changes in Group A and Group B, it can be found that the team with the more formation changes will have a relatively higher number of effective formations and duplicate team rows, with the average effective formation of Group A and Group B being 15 and 19 respectively.

Table 3. Number of complete action formation changes

Group	Place	Complete set of action												Y	B	C	B	T
		First paragraph		second paragraph		Third paragraph		Fourth paragraph		Fifth paragraph		Sixth paragraph						
		X1	X2	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2					
A	1	5	1	2	1	1	-	4	2	5	3	4	-	19	65%	11	35%	30
	2	6	-	4	1	1	-	4	2	5	1	3	-	17	81%	5	19%	20
	3	5	1	3	3	1	-	3	-	4	3	2	-	17	74%	7	26%	20
	4	6	-	2	2	1	-	4	-	4	2	2	-	18	79%	6	21%	21
	5	7	-	2	2	1	-	5	-	3	1	3	-	19	78%	6	22%	24
	6	5	-	3	1	1	-	3	-	2	1	4	-	12	67%	7	33%	18
	7	7	1	4	1	1	-	3	-	3	-	2	2	8	58%	6	42%	15
	mean	5.8	0.1	2.9	1.6	1	-	3.7	4	3.7	1.8	2.9	2	15.00	72%	6.86	28%	21.1
		7	4	4	10			5	8	8	5	8	5					
B	1	2	-	4	1	5	1	3	1	5	1	-	-	18	82%	18	18%	22
	2	2	1	4	1	5	2	3	2	6	1	-	-	19	76%	19	24%	25
	3	2	-	5	-	4	1	5	1	7	-	-	-	21	81%	21	19%	26
	4	2	1	4	-	4	2	3	2	6	3	-	-	21	81%	21	19%	26
	5	3	-	4	-	5	1	3	1	5	3	-	-	19	73%	19	27%	26
	6	2	-	4	-	5	2	3	2	6	2	-	-	17	65%	17	35%	26
	7	2	-	4	-	5	2	4	2	8	2	-	-	18	69%	20	26%	27
	8	2	-	4	-	4	1	4	1	6	1	-	-	20	74%	18	31%	26
	mean	2.1	0.2	4.1	0.2	4.6	1.5	3.5	1.3	6.1	2.1	-	-	19.13	65%	6.36	25%	25.5
		3	5	3	5	3	0	0	8	3	3							

3.3.3. Selection of types of formation changes. The movement trajectories of the cheerleading set movement formation changes are shown in Table 4. The data in the table were tallied for all the players of each team by exploring the movement routes of all the players in that team during the formation changes by slowing down the video. The mean value of the left-right movement routes for Group A was 11.4 times, the mean value of the forward-backward movement routes was 6.6 times and 7.3 times, respectively, while the mean value of the diagonal and arc movements was less than 1 time. The total number of times the teams in Group B moved their routes did not differ much, with a mean value of 43.6 times for the 8 teams, indicating that the coaches in Group B were very good at designing moving routes using moveable paces. The number of times that Team B moved the route left and right was 18.13 times, and the number of times that they moved forward and backward was 2.5 times and 3.8 times, respectively, and they lacked the design of moving routes in diagonal and arc lines. The uneven use of front-back, right-left and left-right movement routes and the obvious use of diagonals and arcs in Groups A and B indicate that the teams made greater use of the playing field.

Table 4. The mobile route of the set of action formation changes

Group	Place	Front	After	Left	Right	Diagonal	Arc	Total amount
A group	1	10	11	16	16	2	-	55
	2	7	7	13	13	2	-	42
	3	7	9	13	13	-	-	42
	4	7	8	12	12	-	2	41
	5	7	8	10	10	1	-	36
	6	5	6	9	9	-	2	31
	7	3	2	7	7	-	-	19
	mean	6.6	7.3	11.4	11.4	0.71	0.57	38
B group	1	3	7	18	18	2	2	50
	2	2	2	20	20	2	-	46
	3	2	4	18	18	1	-	43
	4	3	4	17	17	1	-	42
	5	3	4	18	18	-	-	43
	6	2	2	18	18	2	1	43
	7	2	3	18	18	-	-	41
	8	3	4	18	18	-	-	41
	mean	2.5	3.8	18.13	18.13	1.14	0.43	43.63

3.3.4. Space utilization for formation changes. The spatial utilization of the changes in the formation of college cheerleaders' sets of movements is shown in Table 5. The use of high and low level formations can not only improve the visual effect of set movements, but also increase the ornamental value of the performance of set movements and make the set movements full of freshness. In order to present the visual effect of high and low levels in the set movements, it is necessary to reasonably utilize the three-dimensional space when designing the formation. According to the rules of cheerleading competition, the space of formation can be divided into three major categories: A-ground, B-standing, C-empty. Through the table, it can be seen that on the basis of keeping the originality of the movement, each team utilized the space types more reasonably according to their own ability.

Table 5. The space utilization situation of the complete set of movement formation change

Group	Place	A-B	B-A	B-C-B	B-C-A	B-A-B	Total(secondary)
A group	1	1	3	1	-	1	6
	2	1	4	1	1	1	8
	3	1	5	2	1	3	12
	4	1	2	2	1	4	10
	5	-	2	2	1	2	7
	6	-	3	-	-	2	5
	7	1	3	-	-	-	4
B group	1	1	6	1	2	1	11
	2	1	6	1	1	-	9
	3	-	3	-	1	-	4
	4	1	5	-	-	-	6
	5	-	4	1	2	1	8
	6	1	3	1	1	1	7
	7	-	4	1	2	1	8
	8	1	5	1	1	-	7

4. Conclusion

This paper proposes a multi-objective path planning model for college cheerleading formations, and negotiates with other cheerleaders according to the intensity of willingness to get an achievable coordination decision for cheerleading formations. Subsequently, the MOPSO-CA algorithm is proposed for the multi-objective planning model and applied to the college cheerleading formation scheduling and transformation, and finally simulation experiments are carried out to verify the results using Matlab. The results are as follows:

1) The MOPSO-CA algorithm can not only ensure that the direction angle of the cheerleading team members tends to the direction angle of the cheerleading team leader, successfully avoiding obstacles, but also ensure that the positional error of the cheerleading team members tends to zero.

2) The design of college cheerleading squad should focus on four basic elements: first, the number of squad changes is reasonable, and the type of squad is rich; second, make full use of the mobile action to increase the number of squad changes; third, keep the originality of the action, and the use of the squad's mobile routes and space; fourth, make full use of the mobile pace, and reasonably design the number of squad changes.

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