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Study on Swarm Robots Aggregation Formation Control

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Abstract: This study puts up dynamic aggregation formation control strategies over swarm robots when the robots are in uncertain environment. The clustering centers of the swarm robots are determined by combining the K-means clustering algorithm and the composite body structural formation control strategies. Individual robot takes the formation control rows spontaneously generated from local detection as the vector to head toward the target and avoid obstacles. Those robots aggregating in a form of circle centered a clustering center will further form into a formation of a triangle. The simulation tests and other tests against the forming and change of the swarm robots aggregation formation have verified the validity and feasibility of the proposed strategies.

Key words: Swarm robots, K-means clustering algorithm, formation control, coordination

INTRODUCTION

Many species move in certain forms, such as ants, bees, birds, fish, etc., i.e., these animals move in some geometrical formations or with a relatively invariable formation, which enables the animals to seek for food, hunt for preys and fight against predators by their joint effort and which is biologically important for the their survival and reproduction (Gu, 2008; Weimerskirch *et al*., 2001). Enlightened by the complex behaviors of social species, the research on swarm intelligence has received quite attention in the field of control and artificial intelligence (Xu *et al*., 2009). If the swarm robots can maintain a certain formation to complete tasks and can form into the formation automatically, they will play indispensable roles in various fields. For example, the swarm robots can replace the soldiers to perform military missions in severe and dangerous circumstances in militarily reasonable formations. And in the field of aeronautics and astronautics, the swarm robots can explore unknown areas by maintaining a certain formation at low expense. Therefore, the aggregation formation control strategies of swarm robots are quite promising in wide applications.

Currently the major formation control methods include the leader-follower method, behavior-based method, virtual structure method and generalized coordinates method (Beard *et al*., 2001; Lawton *et al*., 2003). These methods lay particular emphasis on how to make the swarm robots maintain a certain formation in moving and usually these methods are just applicable to a small number of robots. Therefore, when the number of robots increases, the methods to control the robots formation need to be improved.

This study probes into the aggregation formation control strategies of swarm robots that how can the swarm robots make quick response in an uncertain environment while they are able to maintain a certain formation without the position of each robot being restrained. By combining the K-means clustering algorithm with the composite body formation control strategies, this study has realized the aggregation formation control over a large scale of swarm robots, avoiding collision among the robots in the course of them heading toward the clustering center and enabling the robots to complete tasks in a certain formation by fast aggregation.

BEHAVIOR-BASED CONTROL OVER SWARM ROBOT

Balch and Arkin first put up the behavior-based method (Balch and Arkin, 1998). The behavior-based method enables the swarm robots to generate the required whole behaviors via designing the robots' basic behaviors and following local control rules (Lei *et al*., 2008). The composite body structure is a typical behavior-based control strategic behavior (Tan *et al*., 2005), which takes each robot as a composite body and each composite body is a self-organized computing element. The composite bodies are connected in a two-way interactive manner by the robots' streak-lines and each composite body

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performs self-organization based on the feedback and guide from the adjacent composite bodies. The concurrent behaviors of these composite bodies give rise to a dynamic balance, in which all the composite bodies under behavioral control will not undergo drastic transformation. The K-means clustering algorithm is a supervised learning algorithm. It groups unknown data sets, making the data in one data set as similar as possible and the data in different data sets as different as possible (Qu *et al*., 2011). At one certain time, set in a certain Euclidean Space $x_1, x_2, \ldots x_i$ ($i = 1, 2, \ldots n$), which in order represents Robot 1, Robot 2, …, Robot n. Sensors are installed in an evenly spaced manner on the outboard of each robot's body, which help the robots detect if there are robots in the neighboring areas and, if any, the position of these robots. The robots send messages to each other via their streak-lines.

The algorithm flow applying K-means clustering algorithm to the behavior control of swarm robots in uncertain environment is as below:

- Randomly select several robots (numbered from Robot 1 to Robot k) among all the robots (numbered from Robot 1 to Robot n, n = k) to be the initial clustering centers m_i ($i = 1, 2, \ldots, k$)
- Calculate the Euclidean distance d (i, j) between the clustering center m_i and Robot x by Eq. 1:

$$d(i,\ j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \ldots(x_{in} - x_{jn})^2} \tag{1}$$

where, $i = (x_{i1}, x_{i2}, \ldots, x_{in})$ and $j = (x_{j1}, x_{j2}, \ldots, x_{jn})$ are two n-dimensional data objects.

- The robots (numbered from Robot 1 to Robot n) find out their shortest distance d (x_i, m_i) from the clustering centers m_i (numbered from m_1 to m_k) and these robots (numbered from Robot 1 to Robot n) are, respectively attributed to the same clusters as m_i is
- After all the objects are ergodic, use Eq. 2 to recalculate the values of clustering centers m_i to generate the new clustering centers:

$$m_k = \sum_{i=1}^{n} \frac{x_i}{n} \tag{2}$$

where, m_k represents the clustering center of Cluster k and n represents the number of objects in Cluster k.

The squared error criterion enables the clustering results to be independent and compact as much as possible, i.e., the similarity of the objects in one cluster is as high as possible. Eqution 3 as below for details:

$$E = \sum_{i=1}^{k} \sum_{n \in \mathrm{sl}} |n - m_i|^2 \tag{3}$$

where, E represents the sum of the squared errors of all objects, n represents the objects in the space and m_i represents the mean value of Cluster c_i.

By the above steps, the K-means clustering algorithm is combined with the composite body formation control strategies to control the aggregation formation behaviors of swarm robots.

AGGREGATION FORMATION CONTROLOVER SWARM ROBOTS

It is the tasks that determine the behaviors of swarm robots. When the robots cooperate with each other to complete a task, it requires the robots to move from their initial positions to the target positions to form the target formation without colliding with the static robots or robots in motion. Based on the K-means algorithm, four categories of basic behaviors of swarm robots are generated by the composite body structural behavioral control strategies (Yang *et al*., 2009), including moving to the goal, avoiding the static obstacles, avoiding the robots and maintaining the formation. Each category of behavior outputs a series of control parameters which further generates related functions. Based on the change of actual environment, these functions output values according to relevant information and determine the vectors to adapt to the environment. The vectors and control parameters of the four categories of behaviors are as follows:

- **Move_ to_ goal:** The vector of robot moving to the goal is calculated by Eq. 4, which is the vector from a robot's current position to its target position. The control parameters of "move _to_ goal" change with that of the value of d_1, the distance of the robot's current position to the target position. Equation 4 is as follows:

$$V_{More\_to\_goal} = \frac{1}{\sqrt{(x_g - x_c)^2 + (y_g - y_c)^2}} \begin{bmatrix} x_g - x_c \\ y_g - y_c \end{bmatrix} \tag{4}$$

The control parameters are obtained by Eq. 5:

$$f_1(d_1) = \begin{cases} a_1 & d_1 \in [0, s\_max] \\ a_1(s\_max^2/d_1^2) & d_1 \in [b_1, s\_max] \\ a_1(s\_max^2/b_1^2) & d_1 \in [0, b_1] \end{cases} \tag{5}$$

where, $[x_g, y_g]^T$ is the coordinate of the target position, $[x_c, y_c]^T$ is the coordinate of a robot's current position. a_1 and b_1 are adjustable and b_1 is related to the step length of the robot. s_max is the maximum detection range of the sensors installed on the robot.

Avoid _static_ obstacle: The vector of robots avoiding static obstacles is calculated by Eq. 6. When a robot detects obstacle in the collision prevention area by sensors and the absolute value of the difference in angle between the robot's current moving vector and the line from the robot to the obstacle is less than 90 degrees, it can be considered that the obstacle might hinder the robot's movement. The vector of robots avoiding static obstacles $V_{Avoid\ static\ obstacle}$ enables the robot to change its direction so as to prevent collision with the obstacle. Equation 6 is as follows:

$$V_{Avoid\_static\_obstacle} = \begin{bmatrix} \cos(\pm(\theta+\alpha)) & -\sin(\pm(\theta+\alpha)) \\ \sin(\pm(\theta+\alpha)) & \cos(\pm(\theta+\alpha)) \end{bmatrix} \begin{bmatrix} x_d \\ y_d \end{bmatrix} \quad (6)$$

The control parameters are obtained by Eq. 7:

$$f_s(d_s)|_{s=2,3} = \begin{cases} 0 & d \in \phi \\ a_1\ (s-\max/d_s - r)^{index} & d_s \in (b_3, s-\max) \\ a_1\ (s-\max/d_r - r)^{index} & d_r \in [0, b_1] \end{cases} \quad (7)$$

where, θ_s is the angle between the robot's current moving vector and the line from the robot to the obstacle, ± indicates the angle by which the robot changes his direction (to left or to right), $[x_d, y_d]^T$ is the moving vector of the robot; a_1 and b_s are adjustable and b_s is related to the radius of the robot; d_2 is the shortest distance between the robot and the obstacle area; d_3 is the shortest distance between the current robot and the nearest robot to it. The value of index is 2 when the detected object is a static obstacle or other robots and 3 when it is obstacles in motion.

Avoid_ robot: The vector of robots avoiding obstacles in motion is calculated by Eq. 8. When a robot is detecting other robots which might influence its movement, it will comprehensively consider its current position and the predictable position to form an obstacle area, based on which the robot will make decision to rotate by a certain angle to the left or to the right to avoid colliding with the robots. Equation 8 is as follows:

$$V_{Avoid\_robot} = \begin{bmatrix} \cos(\pm(\theta_m+\alpha)) & -\sin(\pm(\theta_m+\alpha)) \\ \sin(\pm(\theta_m+\alpha)) & \cos(\pm(\theta_m+\alpha)) \end{bmatrix} \begin{bmatrix} x_{d-p} \\ y_{d-p} \end{bmatrix} \quad (8)$$

The output control parameters of robots avoiding other robots and those of robots avoiding static obstacles are the same, shown as Eq. 7.
where θ_m is the largest angle between the predicted vector of an obstacle and the line from the robot to the obstacle area, ± is determined by the relative correlation between the predicted vector of the obstacle and the obstacle area and $[x_{d-p}, y_{d-p}]^T$ is the moving vector of the obstacle predicted by the robot.

Keep_formation: Each robot calculates its ideal position $[x_{fg}, y_{fg}]^T$ in the formation based on the position information of the clustering centers, which will become the target position for the robot in its next move. When the current position of the robot $[x_c, y_c]^T$ is mismatching with the target position, i.e., the condition meets, $\sqrt{(x_{fg}-x_c)^2+(y_g-y_c)^2} > \varepsilon$ the vector of robots keeping the formation can be calculated by Eq. 9 as follows:

$$V_{keep\_formation} = \frac{1}{\sqrt{(x_{fg}-x_c)^2+(y_{fg}-y_c)^2}} \begin{bmatrix} x_{fg}-x_c \\ y_{fg}-y_c \end{bmatrix} \quad (9)$$

The control parameters are obtained by Eq. 10:

$$f_4(d_4) = \begin{cases} a_4 & d_4 \in [b_4 + \infty] \\ (a_4/b_4)d_4 & d_4 \in [0, b_2] \end{cases} \quad (10)$$

where, a_4 and b_4 are adjustable and d_4 is the distance between the current position of the robot and its ideal position in the formation.

The above four categories of control parameters can eventually determine the movement speeds and vectors of the robots. Considering that obstacles (numbered from 1 to q) may hinder the robots' movement, the final movement vector of robots is decided by Eq. 11 as follows:

$$\begin{cases} V_{direction} = \text{normalize} \\ f_1(.)\ f_{q-0}(.)\ f_3(.)\ f_4(.) \begin{bmatrix} V_{More-to-foal} \\ V_{q-obstacles} \\ V_{Avoid-robot} \\ V_{Keep-formation} \end{bmatrix} \\ f_{q-obstacles} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \max_{t=1}^{q}\ f_2^t(.) \\ V_{q-obstacles} = \text{mormalize}\ (\sum_{t=1}^{q} f_2^t(.) V_{Avoid\_robot}^t) \end{cases} \quad (11)$$

where f_2^t (.) and $V_{Avoid\_robot}^t$ are respectively the function and output vector generated by the control parameters of collision prevention behaviors considering a single obstacle t (t = 1, 2, 3, ..., q). f_0^t (.) and $V_{q\_obstacles}$ are, respectively the control parameters and vector of collision prevention behaviors considering the obstacles numbered from 1 to q.

The clustering centers of robots are not required to keep the formation without a special coordinator; therefore, the ideal moving step length of the robots is indeterminate. The robots flexibly choose the clustering centers based on the formation errors. In moving toward the target clustering centers, the step length of a robot step (.) is a variable determined by Eq. (12) as follows:

$$\text{step}(.) = \begin{cases} 0 & \gamma \notin [0, \frac{\pi}{2}],\ \gamma \in [0, \frac{\pi}{2}] \cap (B_1 = 0) \\ \min(d_{c\_d} \cos(\gamma),\ \text{step} - \max) & \gamma \in [0, \frac{\pi}{2}] \cap (B_1 = 0) \\ \min(d_{c\_d} \cos(\gamma),\ \text{step} - \max) & B_1 = 1 \end{cases} \tag{12}$$

where, B_1 is a Boolean variable, whose value is 1 when a robot detects an obstacle in motion; is the angle between the final vector of the robot and its vector to its ideal formation position; d_{c_d} is the distance from the robot's current position to the ideal position in the formation; step_max is the longest step length of the robot.

After the robot obtains information on synthesized moving vector and ideal moving step length, it can determine the actual step length in the vector based on information of the current environment to make final decision on movement.

CONTROL ALGORITHM FLOW

The control algorithm flow of individual robot based on the K-means clustering algorithm and composite body structure formation control is shown in Fig. 1.

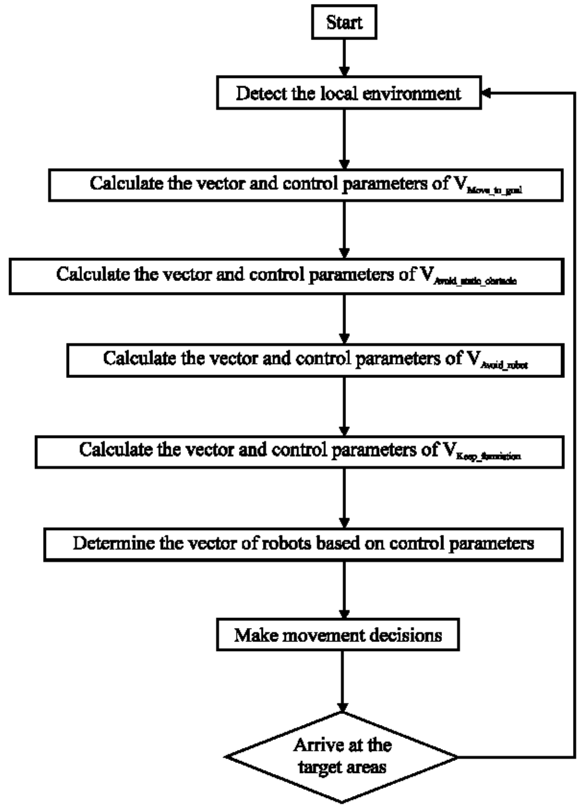

Fig. 1: Control algorithm flow of individual robot

Table 1: Values of control parameters

Function generated by control parameters	α	β
$f_1(.)$	1	0.25
$f_2(.)$	1	0.30
$f_3(.)$	1	0.30
$f_4(.)$	2	1.00

SIMULATION OF AGGREGATION FORMATION CONTROL OVER SWARM ROBOTS

This study adopted simulation test to verify the proposed aggregation formation control method. The robots are round with radius being 0.2. 400 robots are selected to conduct the simulation test. The radius of the sensory area is 1.8 and the longest step length is 0.5. The task for the 400 robots is to move to the clustering center from their initial positions without any collision and aggregate to form into a triangle. The value of α in the "avoid static obstacle" and "avoid robot" behaviors is $\pi/6$. The values of robot's behavioral control parameters are shown in Table 1.

Figure 2 is the simulation process of robots aggregation movement. In Fig. 2a, the swarm robots are scattered in the space in a quite chaotic manner. First of all, the scattered robots randomly select three clustering centers in the space when the "move_ to_ goal" behaviors take the leading role. The four categories of control parameters $V_{direction}$ determine the robots' moving speeds and vectors. The robots move to the clustering centers actively while the K-means clustering algorithm will recalculate the centroid of each cluster. Once the clustering center is changed, the robots will immediate move to the new target. When the robots are moving near the clustering centers, the "keep_formation" behaviors become dominant. The robots maintain the formation of a circular shape. Because the robots belong to different clustering centers, the robots belonging to one clustering center do not subject to the control and restraint of other clustering centers. These scattered robots will indistinctly produce effective group behaviors that can generate a fitness function after more than 25 times of iteration (each iteration lasting for 1 sec), shown as Fig. 2b. With the evolvement of group movement strategies, the

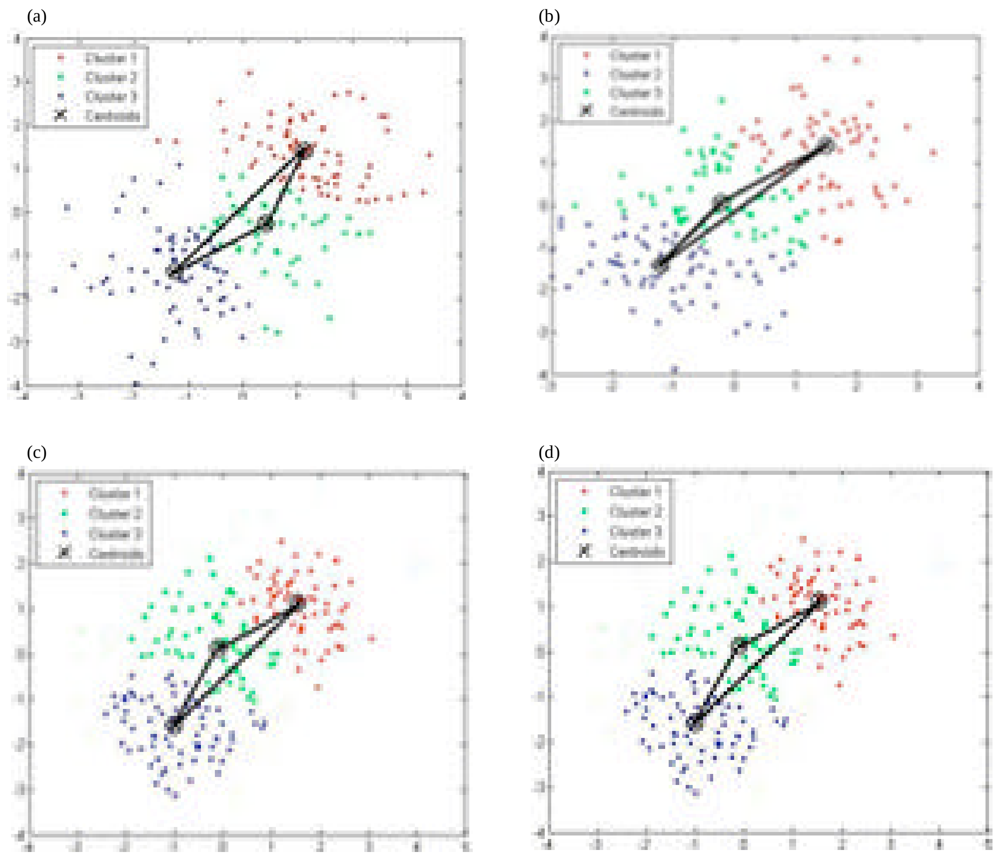

Fig. 2(a-d): Simulation process of aggregation formation control, (a) t = 0sec, (b) t = 25 sec, (c) t = 121sec and (d) t = 225sec

movement trajectories of robots have gradually become smooth. After 121 times of iteration (121 sec), the coordination among the robots becomes significant that distinct aggregation can be observed near the clustering centers, shown as Fig. 2c. After 225 times of iteration (225 sec), it is observed that the swarm robots have generated a spiral behavior around the target position, shown as Fig. 2d. This is because that among the many selected individual robots with high fitness, the vector of the joint repulsion does not direct to the target position. In spite of slight oscillation, 450 times of iteration (450 sec) later the fitness of the swarm robots has reached a higher level and the robots belonging to each clustering center have aggregated into a circular shape and the three clustering centers with robots further form into a triangle, shown as Fig. 2f.

FULL-SCALE EXPERIMENT OF SWARM ROBOTS AGGREGATION AND COORDINATING

An experiment platform of swarm robots cooperation system is established to conduct the experiment of swarm robots aggregating and coordinating to complete tasks based on the combination of K-means clustering algorithm with composite body control strategies.

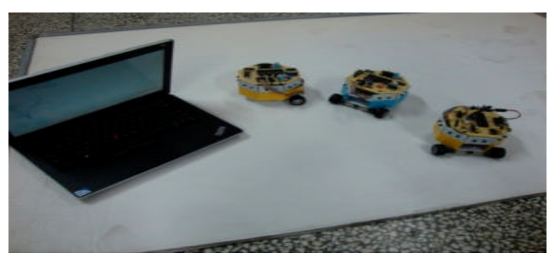

Fig. 3: Hardware platform of swarm robots coordinating experiment system

Experiment platform of swarm robots aggregating and coordinating: The "hardware platform of swarm robots coordinating experiment system" developed by us is composed of three robots, shown as Fig. 3.

This platform is developed based on the Keil Software-produced Keil C51 C language platform, relying on the cooperation between the epigynous computer and hypogynous computer. The programming language is C language. After the programs are developed and debugged on the Keil C51 platform, the programs written in C language is written into the hypogynous computer which further translates the program codes in C language into hex codes to control the whole system.

Experiment of swarm robots aggregating and coordinating: The algorithm flow of aggregation formation control is as follows:

- Initialize the initial position of each robot and the initial target position in the formation
- Establish the environment set of each robot based on the local information
- Update the elements in the environmental set based on the dynamic environmental information
- Calculate the vector to the target to generate the optimum speed
- Recalculate if conflict occurs
- Enable the robots to move toward each one's target if no conflict occurs
- Stop the robots if the aggregation task is completed; otherwise go back to step 3

In the experiment the three robots were randomly scattered on a 1×1m experiment board. In the aggregation process, the robots can detect other two robots as well as the frames of the board. If detecting the latter, the robot would adjust its moving vector until it cannot detect the frames. If one robot conflicts with another robot in the task, the robots would exchange their speeds and location via communications and negotiation. The robots would continue to move after reaching an agreement. The algorithms of aggregation tasks include the frame aggregation algorithms to guarantee that similar robots aggregate together and different robots stay away from each other as far as they can.

The mutual detection and information exchange among the robots entails that the three robots scattered in the space move in a line. The three robots in the experiment are named A, B and C. First of all, let A, B and C move in accordance with their initial vectors as is shown in Fig. 4. Assume the vector shown in Fig.4 as the positive vector. If a robot rotates clockwise, consider the turned angle as negative value, otherwise positive. When B is detecting that A stops moving and at this moment B is on the left to A's moving vector, B will contra-rotate by 10°. B keeps moving and repeats the aforesaid detection

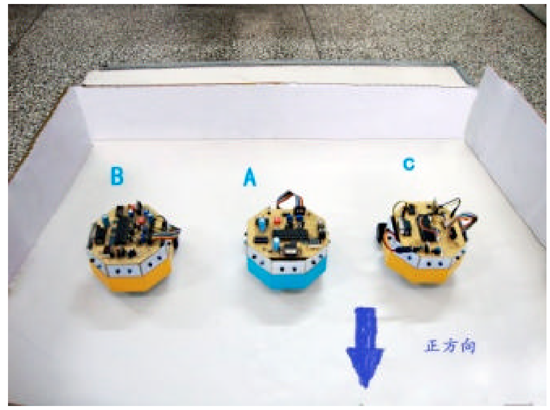

Fig. 4: Formation

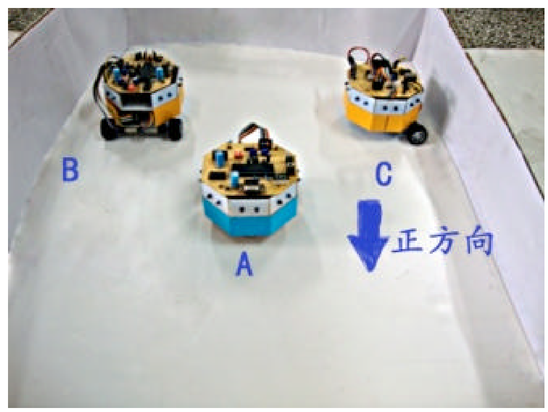

Fig. 5: Formation of a in a line triangle

until the wheels of B just face the positive vector shown in the figure. C performs the detection as B does and adjusts its moving vector by rotating clockwise. When the three robots are all moving along with the positive vector, the sensors on the sides of robots start to detect each other. B and C move by taking A as the benchmark. The signals detected by B and C are transmitted back to the main control chips so that the three robots can decelerate and stop in the shortest time and distance, when A, B and C can move simultaneously in a line as is shown in Fig. 4.

The robots will maintain a balance after they move in a line. Then it is required that the robots form a triangle formation. A will accelerate. B and C will move without changing their speed if they cannot detect A and A will move at the accelerated speed if it cannot detect B and C, as is shown in Fig. 5.

In the full-scale swarm robots experiment, the robots aggregated to form a line and a formation of a triangle by clustering algorithm programs, obtaining expected effect and realizing aggregation formation control. However, there are still some shortcomings as below:

- In the experiment, the actual positions of the robots significantly deviate from those positions in the simulation test after the robots have moved for a while. The analysis shows cause for the deviation that in the simulation test the external factors are not considered while in the actual movement, there is sliding friction between the wheels of the smart robots and the floor, i.e., the inertia of the robots is inevitable. When a robot is igniting, accelerating, decelerating and rotating, it is not sheer rolling between the wheels and the floor, thereby costing some displacement distance. Such cost distance keeps cumulated in the movement, giving rise to the final deviation aforementioned. In the experiment, such deviation can be reduced by properly decelerating the robots
- In the experiment, the initial positions of the three robots can exert significant influence on the experiment results. The vector that each robot is toward at their initial position determines the speed to complete the task. The continuously cumulated error in the experiment might lead to failure of the task after the system has run for a certain period. Therefore, in the established coordination system of swarm robots, the initial vectors of the robots shall be as the same as possible

CONCLUSION

- This study proposed the swarm robots aggregation formation control strategies by combining the K-means clustering algorithm with the composite body formation control strategies, realizing aggregation formation control over large-scale swarm robots. Four categories of behaviors were introduced to prevent the robots from colliding when they are moving toward the clustering centers to fast aggregate into the target formation to complete the task. The four categories of behaviors include moving to the goal, avoiding the static obstacles, avoiding the robots and maintaining the formation. The full-scale swarm robots experiment verified that the robots can aggregate in a line as well as in a formation of triangle by the clustering algorithm programs, obtaining the expected effect
- The distributed control strategies were adopted to guide the robot in the aggregation. Each robot generated independent strategies based on their local detection; therefore, the control strategies excel at scalability

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