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AGGREGATION BEHAVIOR OF MOBILE ROBOTS IN A SWARM CONTROL ALGORITHM UNDER NATURAL CONSTRAINTS

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Abstract. For a group of mobile robots in free space, we consider aggregation under the assumption that each robot has information about the position and course of the nearest neighbors only (without any additional information, such as the group target). This problem is the first stage of a mission carried out by a group of robots; it can be solved under certain conditions, see below. We propose a swarm control algorithm based on the metric-topological approach under maneuvering constraints. The sizes and configurations of the arenas are chosen, and initial position requirements are specified for robots. The characteristics of robots are selected, and computer simulations are conducted to evaluate the model parameters for the required directional coordination level of swarm motion without clustering and with a safe distance between robots during the entire mission.

Keywords: swarm robotics, aggregation, alignment, simulation modeling.

INTRODUCTION

Aggregation is one of the most fundamental manifestations of swarm behavior in nature. In a natural swarm, animals need to stick together; otherwise, the swarm will split into several parts and shrink in size (eventually, its survival may be jeopardized). Aggregation is often needed for many robotic systems as well, being a prerequisite for other joint actions. In addition, splitting a swarm into separate parts (clustering or loss of swarm connectivity) may fail the group task.

Aggregation is possible through either a signal or self-organization. In the former case, a swarm gathers at locations determined by signals from the environment (e.g., the warmest or brightest place, etc.). Based on the behavior of young honeybees, BEECLUST [1] is the first and most popular algorithm of this kind for robots.

In the latter case, the well-known examples in nature are flocks of birds, schools of fish, etc. In the classical paper [2], C. Reynolds first presented a distributed behavioral pattern of such a flock for computer simulations. His self-organized coordinated motion model of a group of autonomous mobile objects provides three simple velocity and course control rules describing the maneuvering of individual objects based on the positions and velocities of their nearest neighbors: repulsion (avoiding collisions with neighbors), alignment (moving in the same direction as neighbors), and attraction (maintaining the same distance between neighbors without swarm separation). The three rules were used in subsequent works in different combinations and variations.

Swarm robotics has emerged as an approach to perform a task using several robots with limited and simple capabilities. Such robots move, make independent decisions without external influence, interact with their environment, and establish local interaction with each other.

In this paper, aggregation is treated as the first stage of a task performed by a group of mobile robots, and the control algorithm will be based on the principles of swarm robotics.

Many different methods and algorithms implement self-organized aggregation behavior in swarm robotics.

Among probabilistic approaches, *probabilistic finite-state machines* (PFSMs) are common. In [3], *particle swarm optimization* (PSO) was applied to optimize the parameters of a PFSM controller. The authors [4] studied aggregation when adding a certain share of informed robots and analyzed how many of them are needed to direct the aggregation process to a given domain among the available ones in the environment.

The paper [5] introduced a microscopic aggregation behavior model based on the virtual expectation of robots concerning cluster size. This model involves a communication mechanism that helps robots estimate the cluster size and guides them to the desired cluster. Once a robot detects the desired cluster, it tries to move closer to it. Note that the direction of movement is determined using the mean wave travel method.

Another widespread approach is based on pairwise interaction between robots through artificial forces. In the publication [6], a virtual attraction/repulsion force model was considered to study aggregation based on local interaction. In most of such works, the distance between robots is the only factor taken into account for robot aggregation. At the same time, some researchers include additional factors such as the density of robots in a swarm. For example, a self-organizing aggregation method based on the *Distance-Minkowski K-Nearest Neighboring* (DM-KNN) metric with density estimation was proposed in [7]. The interpolation of *smoothed particle hydrodynamics* (SPH), a method to estimate the density of robots in a swarm, was applied to compute a distance-weighted function. This function became a key factor in determining the k nearest neighbors considered for robot aggregation. A virtual physical connection between neighbors was achieved using a viscoelasticity-based proximity model.

The paper [8] proposed an aggregation method based on self-organized swarm motion. Such aggregation behavior is a decision mechanism that estimates both the distances between neighbor robots and the courses of robots. The goal of this method is to aggregate a swarm of robots randomly placed in an arena bounded by obstacles, forming a single cluster without any central control unit. The algorithm was compared with that of [9] and demonstrated better timing results for different arena sizes, numbers of robots, and their detection radii.

Swarm motion algorithms have been studied in many works, starting with the pioneering publication of C. Reynolds. In the context of this paper, we note the classical work of R. Olfaty-Saber [10] with three algorithms: two for free space and one for the case of obstacles. The first algorithm implements three Reynolds rules but leads to regular fragmentation. The second algorithm augments the first one by introducing a virtual γ agent that considers the group target. Due to this modification, the fragmentation problem was completely solved. The algorithms of [10] aim to maintain equal distances between nearest neighbors; the agents are point-like and have no maneuvering constraints. The same approach is characteristic of most other works on the subject, although some authors (e.g., [11, 12]) introduce constraints on the turning velocity of robots.

Among Russian publications, we mention the work [13] focused on the behavior of a group of similar robots (point agents) in an environment with obstacles. Each robot must move toward the target and maintain the minimum admissible distance to other robots and obstacles. A maximum velocity limit was imposed without any constraints on turning velocity (turns were supposed instantaneous). Also, each robot was assumed to have full information about its neighbors and obstacles within a given circle.

To summarize, we emphasize the following features of research works in this area:

– Traditionally, the aggregation problem is solved within a bounded arena, i.e., with obstacles along its boundary.

– The initial connectivity of robots is not assumed: they form many clusters of different sizes at the initial step.

– Robots can stop and get very close to each other.

– Robots have no maneuvering constraints and are often represented by point agents.

This paper is an attempt to identify the conditions necessary to aggregate robots in an unbounded arena without obstacles and without using additional means such as the group target in [10].

1. PROBLEM STATEMENT

Consider a group of N homogeneous mobile robots in the 2D space. The robots are characterized by the following parameters: minimum and maximum linear velocities, maximum acceleration, maximum angular velocity (turning velocity), dimensions (the diameter of the circumcircle), and the range of communication or sensors. They can be chosen arbitrarily for research purposes or specified precisely for particular robots. This paper involves a single limiting condition: the minimum velocity of each robot is nonzero, i.e., it cannot stop and start moving in the opposite (or any other) direction without spatial maneuvering. Also, a safe distance between robots is introduced, i.e., the distance to which they can converge to each other without affecting the neighbor's motion dynamics. Let the safe distance be nonzero as well, which is convenient when calculating the distances between robots in fractions of the safe distance. The information exchange between robots or the range of their sensors is limited by a given maximum distance $R_{\max}$. Delays and noise are neglected.

Initially, the robots are placed in an obstacle-free rectangular arena without boundaries; the initial velocity and course of the robots are random, and acceleration and turning velocity are zero. The initial velocity is chosen between the minimum and maximum values.

The control algorithm uses the position and course of nearest neighbors within a given maximum distance only, without any additional information (such as the group target). Therefore, initial swarm connectivity is required.

For this purpose and safety requirements as well, two conditions are imposed on the initial position of the robots as follows. First, the minimum distance between any two robots exceeds a given minimum threshold; and second, for any robot, there is a neighbor robot located at a distance less than a given maximum threshold. These conditions are due to maneuvering constraints and the range of communication (sensors).

The problem at hand can be formulated as follows: given a swarm size and the initial position constraints and characteristics of the robots, it is required to select the initial arena size and model parameters so that:

– During the entire mission, the swarm will be connected (no clustering).

– At the end of the mission, the courses of all robots will be sufficiently aligned, i.e., the directional coordination level of swarm motion will exceed a given threshold close to unity.

– The safe distance between all robots in the swarm will be maintained during the mission.

Coordinating the courses of all robots in the swarm does not completely solve the aggregation problem because the distances between robots may differ very significantly. However, under free-space motion conditions, the transition from a sufficiently aligned swarm to a connected one, while maintaining a safe distance and connectivity, is easily implemented by varying the model parameters.

2. MATHEMATICAL MODEL

2.1. Basic Model

As has been mentioned, the model involves the principles of swarm robotics. The motion of an individual robot in the swarm is described by the discrete-time first-order equation

$$r_i(k+1) = r_i(k) + u_i(k)\Delta t \quad (1)$$

with the following notations: $r_i(k)$ and $u_i(k)$ are the position vector and control action of robot i at step k, respectively; Δt is the time increment. In the sequel, the step number k will be omitted whenever no confusion occurs. The control action can be interpreted as the desired velocity vector.

The desired velocity vector is determined based on the pairwise influence of objects on each other. This paper considers a motion algorithm in an obstacle-free space, so only the mutual influence of mobile robots is taken into account. A hybrid metric-topological approach is adopted to detect neighborhood. The peculiarities of identifying neighbors will be discussed below. For the time being, we emphasize that the influence of robots on each other is limited by the maximum distance $R_{\max}$.

Traditionally, repulsion, alignment, and attraction zones are used according to the three Reynolds rules. In most works, these zones do not intersect (Fig. 1a). Here, we choose a model with intersecting zones (as in the paper [14]; see Fig. 1b). The model parameter D specifies the boundary between the repulsion and attraction zones and is often interpreted as the desired distance between the robots; $||r_{ij}||$ is the distance between robots i and j; $R_{\max}$ is the range of the mutual influence of robots; finally, $R^{\text{alg}}_{\min}$ and $R^{\text{alg}}_{\max}$ are some parameters of the algorithm.

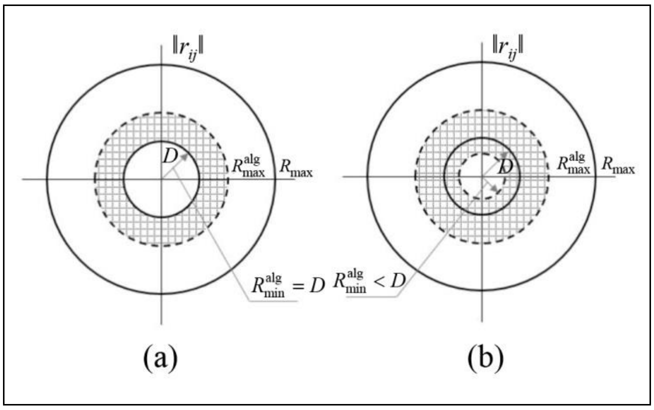

Fig. 1. (a) Non-intersecting and (b) intersecting zones: repulsion (the inner circle of radius D), alignment (the shaded ring with radii $R^{\text{alg}}_{\min}$ and $R^{\text{alg}}_{\max}$), and attraction (the ring with radii D and $R_{\max}$).

Robots within the repulsion zone try to move away from each other, while robots within the attraction zone try to get closer to each other. The alignment zone overlaps with other zones in the vicinity of D and serves to coordinate the courses of robots. Outside the alignment zone, there is only one behavioral pattern: either repulsion or attraction. In the alignment zone, on the other hand, we have two behavioral patterns with some weight coefficients. In general, this model can be written as

$$\tilde{v}_{ij} = \sum_{b\in B} \alpha_{ij}^{b} \tilde{v}_{ij}^{b} \Big/ \sum_{b\in B} \alpha_{ij}^{b},$$

$$\tilde{\vartheta}_{ij} = \arctan\Big(\sum_{b\in B} \alpha_{ij}^{b} \sin\tilde{\vartheta}_{ij}^{b} \Big/ \sum_{b\in B} \alpha_{ij}^{b} \cos\tilde{\vartheta}_{ij}^{b}\Big),$$

with the following notations: $\tilde{v}_{ij}$ and $\tilde{\vartheta}_{ij}$ is the magnitude and direction of the desired velocity of robot *i* relative to robot *j*, respectively; *b* is the set of the main behavioral patterns (rep—repulsion, alg—alignment, and attr—attraction); $\tilde{v}_{ij}^{b}$, $\tilde{\vartheta}_{ij}^{b}$, and α_{ij}^{b} are the magnitude and direction of the desired velocity of robot *i* relative to robot *j* and the weight coefficients for these behavioral patterns, respectively. The values of the coefficients α_{ij}^{b} $(i \neq j)$ are shown in Fig. 2. The robot's self-influence is the reluctance to change its speed: $\alpha_{ii}^{\text{alg}} = 1$ and $\alpha_{ii}^{\text{rep}} = \alpha_{ii}^{\text{attr}} = 0$.

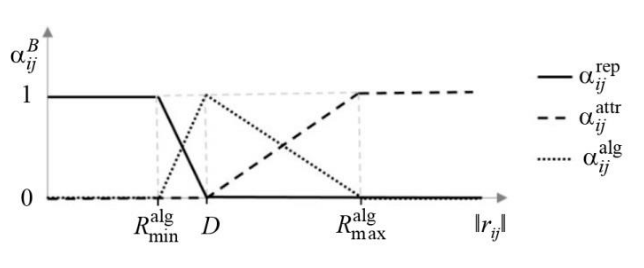

Fig. 2. The coefficients α_{ij}^{b} for different behavioral patterns.

The mutual influence of robots also depends on their dynamic positions, i.e., whether they are ahead of or behind each other (as in the paper [14]). For different behavioral patterns, the desired velocity of robot *i* relative to robot *j* is determined in accordance with Table 1.

The coefficients β_{ij} specify the degree of influence of robot *j* on robot *i* ($\beta_{ii} = 1$) as a function of the distance between them. In this paper, we take the piecewise linear function

$$\beta(x) = \begin{cases} y_{m+1} + \dfrac{y_m - y_{m+1}}{x_{m+1} - x_m}(x_{m+1} - x), \; x_m \le x < x_{m+1} \\ 0, \; x \ge x_4 \end{cases},$$

where *x* is the distance between robots; x_m, y_m, $m = 0, \ldots, 3$, are some parameters; $\beta(x_m) = y_m$; $x_0 = 0 < x_1 < x_2 < x_3 < x_4 = R_{\max}$. The parameter x_4 can be defined as the distance beyond which the influence of robots vanishes.

A separate important issue is the definition of neighborhood. According to [15], each bird in a starling flock interacts on average with a fixed number of neighbors (from six to seven in 3D and from three to five in 2D) instead of all neighbors within a fixed metric distance. Neighborhood is defined not by metric but by topological distance, i.e., by the number of intermediate individuals separating two birds. This approach reflects a characteristic feature of swarm behavior, namely, local interaction. For robot swarms, one possibility is to construct a Delaunay triangulation and determine the nearest neighbors along it, which was actually implemented. Let us define $\sigma_i(k)$ as the set of the nearest neighbors of robot *i* in the triangulation sense (including this robot) at step *k*. Note that the set $\sigma_i(k)$ is time-varying.

Figure 3 provides an example of the nearest neighbors determined by the metric-topological approach used here. For robot 1, the nearest neighbors are the green robots 3–6. Being nearest in the topological sense, robot 2 (green with red border) is nevertheless located far away from robot 1 (the distance exceeds $R_{\max}$); therefore, it is not included in the set $\sigma_i(k)$. The other robots are not nearest in the topological sense. Thus, we have $\sigma_i(k) = \{1, 3, 4, 5, 6\}$.

Table 1

The mutual influence of robots

Behavioral patterns (*b*)	The position of robot *j* relative to robot *i*	The desired velocity vector of robot *i*	
		Magnitude	Course
Repulsion	Ahead of	Minimum	From robot *j* to robot *i*
	Behind	Maximum	
Alignment	Any	Like robot *j*	Like robot *j*
Attraction	Ahead of	Maximum	From robot *i* to robot *j*
	Behind	Minimum	

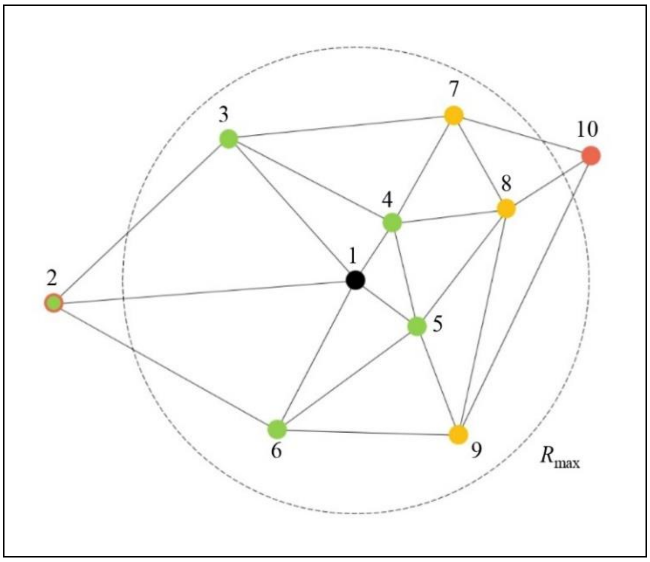

Fig. 3. Nearest neighbors determined by the metric-topological approach.

Finally, the desired velocity $\tilde{u}_i(k)$ is calculated as the total influence of all robots in the set $\sigma_i(k)$ with the coefficients β_{ij}:

$$\tilde{u}_i = \tilde{v}_i \begin{pmatrix} \cos\tilde{\vartheta}_i \\ \sin\tilde{\vartheta}_i \end{pmatrix},$$

$$\tilde{v}_i = \sum_{j\in\sigma_i(k)} \beta_{ij}\tilde{v}_{ij} \Big/ \sum_{j\in\sigma_i(k)} \beta_{ij},$$

$$\tilde{\vartheta}_i = \arctan\Big(\sum_{j\in\sigma_i(k)} \beta_{ij}\sin\tilde{\vartheta}_{ij} \Big/ \sum_{j\in\sigma_i(k)} \beta_{ij}\cos\tilde{\vartheta}_{ij} \Big),$$

where $\tilde{v}_i$ and $\tilde{\vartheta}_i$ are the magnitude and direction of the desired velocity $\tilde{u}_i$; β_{ij} are weight coefficients, $\beta_{ii} = 1$; $\sigma_i(k)$ is the set of the nearest neighbors of robot i, including itself, at step k.

2.2. Maneuvering Constraints

In model (1) with point objects and no maneuvering constraints, the desired velocity u_i equals $\tilde{u}_i$. In this paper, the dimensions of the robots (the diameter of the circumcircle) and maneuvering constraints are considered when calculating the distances and the desired velocity, respectively. In addition, for many robots, there is a safe distance to which they can converge without affecting the motion dynamics of a neighbor robot. Accordingly, a given safe distance D_s is introduced.

The desired velocity u_i in model (1) will be determined under these constraints. For this purpose, we adopt the general expression

$$u_i = f\left(\tilde{u}_i, V_{\min}, V_{\max}, \omega_{\max}, W_{\max}\right), \qquad (2)$$

where a function f transforms the desired control action into an admissible one; $V_{\min}$ and $V_{\max}$ are the minimum and maximum linear velocities; $W_{\max}$ is the maximum acceleration; finally, $\omega_{\max}$ is the maximum turning velocity.

Since the desired control action is interpreted as the desired velocity, the function f can be implemented by calculating the value

$$v_i(k) = \begin{cases} \tilde{v}_i^*(k), & |\tilde{v}_i^*(k) - v_i(k-1)| \le W_{\max}\Delta t \\ v_i(k-1) + \mathrm{sign}(\tilde{v}_i^*(k) - v_i(k-1))W_{\max}\Delta t, & |\tilde{v}_i^*(k) - v_i(k-1)| > W_{\max}\Delta t \end{cases},$$

where

$$\tilde{v}_i^*(k) = \max(\min(\tilde{v}_i(k), V_{\max}), V_{\min}),$$

and the direction of the desired velocity

$$\vartheta_i(k) = \vartheta_i(k-1) + \begin{cases} \tilde{\vartheta}_i^*, & -\omega_{\max}\Delta t \le \tilde{\vartheta}_i^* \le \omega_{\max}\Delta t \\ -\omega_{\max}\Delta t, & \tilde{\vartheta}_i^* < -\omega_{\max}\Delta t \\ \omega_{\max}\Delta t, & \tilde{\vartheta}_i^* > \omega_{\max}\Delta t \end{cases},$$

where

$$\tilde{\vartheta}_i^*(k) = \tilde{\vartheta}_i(k) - \vartheta_i(k-1) + \begin{cases} 0, & -\pi < \tilde{\vartheta}_i(k) - \vartheta_i(k-1) \le \pi \\ 2\pi, & \tilde{\vartheta}_i(k) - \vartheta_i(k-1) \le -\pi \\ -2\pi, & \tilde{\vartheta}_i(k) - \vartheta_i(k-1) > \pi \end{cases},$$

and Δt is the modeling step.

2.3. Swarm Behavior Assessment

Safety is assessed by calculating the minimum distance between robots in the swarm:

$$R_{\min}(k) = \min_{i\ne j}(\| r_i(k) - r_j(k) \| - S)$$

(at step k) and

$$R_{\min} = \min_k R_{\min}(k) \ge D_s$$

(since the beginning of the mission), where S is the dimensions of the robot (the diameter of the circumcircle).

The directional coordination level of swarm motion is calculated as follows:

$$\psi(t) = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j\ne i} \frac{v_i(k)v_j(k)}{|v_i(k)||v_j(k)|},$$

where $v_i(k)v_j(k)$ is the inner product of the velocity vectors of robots i and j at step k. In the ideal state, we have $\psi \approx 1$; in the disordered state, $\psi \approx 0$.

3. SIMULATION MODELING

3.1. Initial Position Requirements and Arena Size

The minimum and maximum distances between any two robots at the initial step are chosen in view of maneuvering constraints. According to experimental results, swarm robotics algorithms can lead to situations necessitating a convergence maneuver between two robots while maintaining a safe distance between them (Fig. 4a). Therefore, the minimum initial distance between the centers of robots is given by

$$D_{\min} = D_s + 4R_t + S = D_s + 4\frac{V_{\max}}{\omega_{\max}} + S,$$

where R_t denotes the robot's turning radius under the maximum turning and linear velocities.

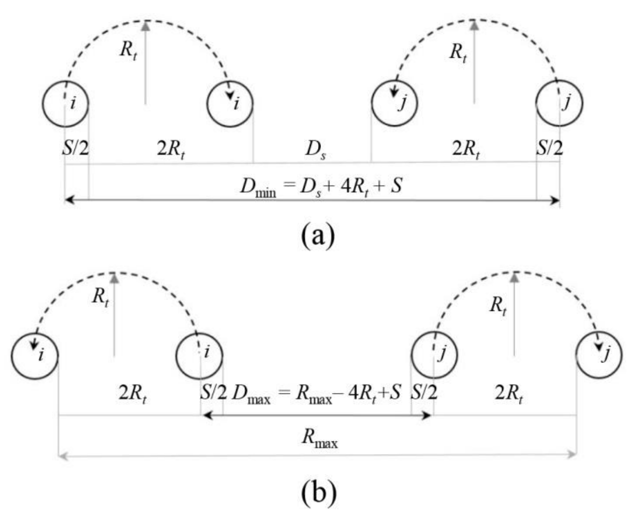

Fig. 4. Maneuvers: (a) convergence and (b) divergence.

Similarly, a divergence maneuver of two robots is possible, during which connectivity must be preserved (Fig. 4b). The maximum initial distance between the centers of the robots is given by

$$D_{\max} = R_{\max} - 4R_t + S = R_{\max} - 4\frac{V_{\max}}{\omega_{\max}} + S.$$

The size of the arena is chosen depending on the number of robots in the swarm (N) and the maximum initial distance between their centers ($D_{\max}$). For computer simulations, we take a swarm of 20 robots and an arena composed of 20 square boxes with a diagonal of $D_{\max}$. Three possible arena configurations are considered: 5 × 4, 10 × 2, and 20 × 1 square boxes. Two variants are also considered: the robots are placed at given locations, and only their initial velocity vector is varied.

3.2. The Characteristics of Mobile Robots

We select arbitrary test characteristics without binding to particular robots and investigate the solvability of the problem within the model. Table 2 shows the list of parameters, as well as their values, which were used in computer simulations. The value $R_{\max}$ is large enough to ensure maneuvering with preserving connectivity (on the one hand) and not to cover the entire arena (on the other hand). The visualization of transients is required to understand the operation of the model, so the units of measurement for robots' characteristics were specified in on-screen coordinates. Of course, when building the model for particular robots, the units of measurement must be chosen accordingly.

Table 2

The characteristics of mobile robots

Parameter	Notation	Value	The unit of measurement*
Minimum velocity	$V_{\min}$	1	c.u./s
Maximum velocity	$V_{\max}$	4	c.u./s
Maximum acceleration	$W_{\max}$	1	c.u./s^2
Maximum turning velocity	$\omega_{\max}$	$\pi/6$	rad/s
Robot's dimensions	S	12	c.u.
Communication range (sensors)	$R_{\max}$	300	c.u.
Safe distance	D_s	24	c.u.

**c.u.—conventional unit*

3.3. The Choice of Model Parameters

The most significant parameters of the model are the function $y = \beta(x)$, which specifies the degree of mutual influence of robots depending on the distance between them, and the desired distance D.

According to subsection 3.1, the maneuvers of convergence and divergence are most critical for maintaining a safe distance and connectivity, respectively. This fact predetermines the shape of the function $y = \beta(x)$ in Fig. 5. A steep slope is required on the interval ($x_0 = 0$, $x_1 = D_s + 4R_t$) to avoid collisions and on the interval ($x_3 = R_{\max} - 4R_t$, $x_4 = R_{\max}$) to avoid clustering. The choice $x_2 = D$ corresponds to the desired distance between the robots; at this point, it is natural to assume a minimum of the function $\beta(x)$, equal to y_2. The choice $y_2 = 1$ is not critical. The values of $y_m = \beta(x_m)$, $m = 0, 1, 3, 4$, and parameter D were chosen based on computer simulations.

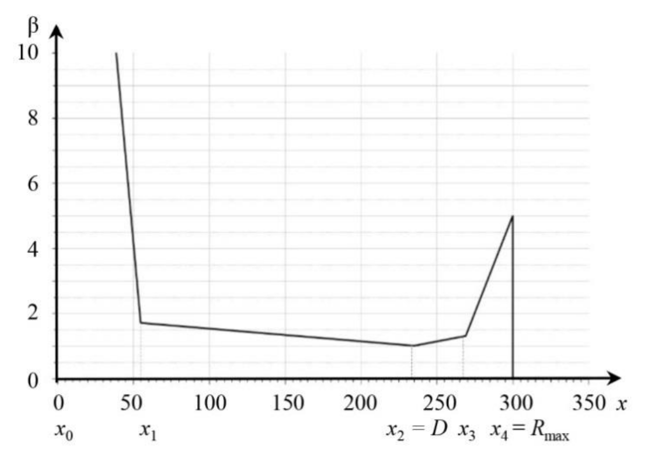

Fig. 5. The graph of the function $y = \beta(x)$, where x is the distance between robots.

The parameters were initially chosen for a 5 × 4 arena. One thousand (1000) simulation runs were conducted under different initial conditions and parameter values, and the most unfavorable ones were determined. A run was terminated upon reaching a given value of the directional coordination level of swarm motion ($\psi \geq \psi_z$ with $\psi_z = 0.92$) or exceeding a maximum number of steps (losing connectivity). For the runs with violated safety, the influence of the parameters y_0 and y_1 on this parameter was analyzed, and new values were assigned accordingly. By analogy, for the runs with lost connectivity, the influence of y_3 and y_4 on this property was analyzed to determine new values. In some cases, it was also necessary to assess the influence and correct the parameter D. This iterative procedure terminated when obtaining the desired results in all 1000 runs; it yielded the basic values of y_m, m = 0, 1, 3, 4, and D for the given characteristics of mobile robots. The parameters were finely tuned on a greater number of runs, 10 000. A similar procedure served to determine the model parameters for a 5 × 4 arena with the chosen characteristics of mobile robots.

Note that the number of unfavorable runs in the iterative procedure did not exceed 0.05% of the total number of runs (5 out of 10 000). In other words, the chosen statistics can be considered sufficient.

Subsequently, the same procedure was executed on 10 × 2 and 20 × 1 arenas. The values obtained for a 5 × 4 arena were chosen as the initial parameter values of the iterative procedure. As it turned out, to pass from a 5 × 4 arena to a 20 × 1 arena, only the value D should be slightly increased to avoid clustering. According to the analysis results, the safety problem was successfully solved, whereas the connectivity problem requires further investigation. In view of the model features, namely, the definition of neighborhood, two initial position variants were identified for robots in a 20 × 1 arena as the most unfavorable ones in terms of possible clustering. In the first variant (*Zig*), the robots are placed in a 20 × 1 arena in the corners of the square boxes in a zigzag pattern; in the second variant (*Line*), the robots are placed on the diagonal of a 20 × 1 arena at equal distances from each other. The distance to the nearest robot is D_{max} in the first case and $(\sqrt{(1+N^2)/2}/(N-1))D_{max} \approx 0.75D_{max}$ in the second case. In these cases, a robot located in the middle of the group has two nearest neighbors and a robot located at the edge has one nearest neighbor. Only the initial velocity vector is randomly changed. For these two variants, similar iterative procedures were executed (10 000 runs each) to determine the values of the parameters y_3, y_4, and D. According to the experimental results, *Line* is the most critical variant in terms of clustering. It requires a rather significant increase in the value of the parameter D, i.e., D = 235, greater than the initial distance between the robots (210). Note that D was chosen as small as possible to obtain a less sparse swarm.

The task was to find the same parameter values for all selected arenas and variants of the initial conditions. Therefore, the parameter values obtained for *Line* (Table 3) were checked for *Zig* and all three arenas. The results are presented in subsection 3.4 below.

Table 3

Model parameters

Parameter	Formula	Value
D	–	235
x_0	–	0
x_1	$D_s + 4R_t$	55
x_2	D	235
x_3	$R_{max} - 4R_t$	269
x_4	R_{max}	300
$y_0 = \beta(x_0)$	–	30
$y_1 = \beta(x_1)$	–	1.7
$y_2 = \beta(x_2)$	–	1
$y_3 = \beta(x_3)$	–	1.3
$y_4 = \beta(x_4)$	–	5
R_{min}^{alg}	–	0.75
R_{max}^{alg}	–	1.25
Δt	–	0.25 s

3.4. Simulation Results

For the chosen values of the model parameters, 10 000 simulation runs were conducted for each of the five variants of the initial position conditions. According to the simulation results, the desired directional coordination level of swarm motion ($\psi_z = 0.92$) was successfully reached in 100% of cases, and a safe distance was maintained as well.

The data in Table 4 and Fig. 6 reflect the rate of reaching a given value of the directional coordination level of swarm motion. In particular, the histogram in Fig. 6 (with a step size of 50) shows the frequency of reaching a given value of this level in a certain number of steps. For the first three variants with *Rand* (a random initial placement of robots), the computer simulations demonstrated an increase in the required number of steps when passing to a more elongated arena. Quite expectedly, the remaining two variants required significantly more time. For these variants, there is a small maximum (about 200 steps for *Line* and 250 steps for *Zig*) coinciding with the maxima for the first three variants; see Fig. 6.

Table 4

The number of steps: statistics

The number of steps	Arena configuration, initial position conditions for robots				
	5 × 4, *Rand*	10 × 2, *Rand*	20 × 1, *Rand*	20 × 1, *Zig*	20 × 1, *Line*
Minimum	96	98	109	31	14
Average	230	251	280	593	557
Maximum	632	636	795	747	661

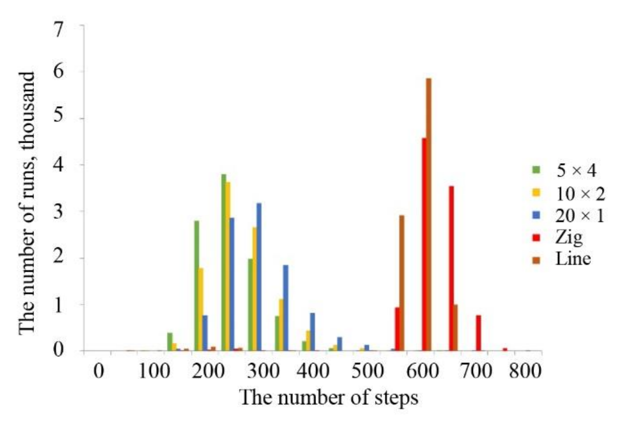

Fig. 6. The rate of reaching swarm connectivity ($\psi \geq \psi_z$).

The data in Table 5 and Fig. 7 characterize safety, i.e., the minimum distance between two robots observed throughout the mission. In particular, the histogram in Fig. 7 (with a step size of $10/D_s \approx 0.42$) shows the frequency of this indicator. Due to the initial position peculiarities in the last two variants, the safe distance is maintained with a margin. For the first three variants, however, the graphs are almost identical. The minimum value exceeds $1.65D_s$, i.e., the safe distance is reached with a margin.

Table 5

The minimum distance (fractions of safe distance): statistics

The number of steps	Arena configuration, initial position conditions for robots				
	5 × 4, *Rand*	10 × 2, *Rand*	20 × 1, *Rand*	20 × 1, *Zig*	20 × 1, *Line*
Minimum	1.69	1.67	1.69	5.17	5.25
Average	2.44	2.4	2.33	7.18	7.63
Maximum	4.15	4.32	3.51	7.65	8.13

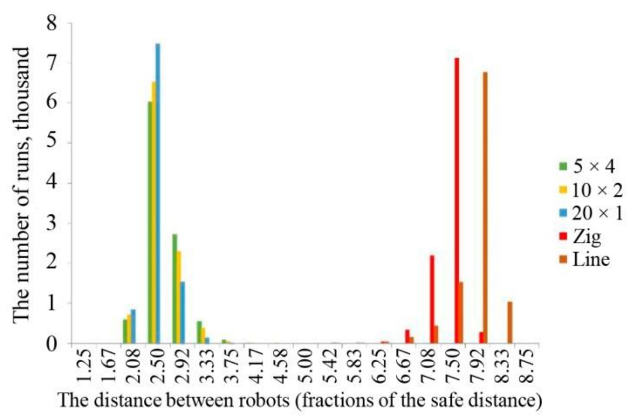

Fig. 7. The minimum distance between robots (fractions of the safe distance).

CONCLUSIONS

The key feature of the problem statement considered above is no use of the so-called group target. (Otherwise, aggregation can be implemented quite simply.) The main difficulty is to maintain swarm connectivity under maneuvering constraints. The absence of the group target significantly complicates the solution and leads to certain requirements for the initial position of robots and the arena size. These requirements essentially depend on the range of communication (sensors) and the characteristics of robots, namely, their maximum velocity and maximum turning velocity. For more maneuverable robots, the arena size increases as they respond faster to the desired course change, thus avoiding loss of connectivity.

The swarm control model proposed in this paper has been validated using randomly selected test characteristics of robots. The model parameters have been successfully tuned to solve the problem for all the arena sizes selected. The results are based on statistical modeling with random initial position conditions for each of the three arenas and two more variants of the initial position on one of the arenas (50 000 simulation runs in total, 10 000 for each variant mentioned).

The model parameters used have different influences on the behavior of a group of robots. Some of them are calculated analytically, and others are assigned based on computer simulations. Moreover, only some parameters have a significant influence, namely, the desired distance between robots and the values specifying the influence function of neighbor robots. In terms of clustering, the most critical case is narrow and long arenas, for which the desired distance between robots must be increased.

This peculiarity affects the applicability of the results for other values of robot characteristics. If the range of communication (sensors) is sufficiently large compared to the distances required for robots to maneuver, only quantitative adjustments to the model parameters will be required in most cases. However, the matter concerns the degree of mutual influence of robots defined in Fig. 5. This condition may be violated for narrow and long arenas and poor maneuverability of robots. In such cases, more stringent constraints must be imposed on the arena size. A potential line of further research concerns the computer-aided selection of model parameters.

Thus, it is possible to model the behavior of a group of robots with given characteristics in advance, determine the minimum and maximum distances, and choose appropriate model parameters to avoid clustering and ensure a safe distance when passing to coordinated motion (i.e., when forming a swarm). This task is the first stage of a mission carried out by a group of robots; it can be performed under some conditions (see above). Only the position and heading information of nearest neighbors (in the metric-topological sense) is used, without introducing any additional information (e.g., the group target).

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