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Bioinspired Method of Agent Redistribution between Groups

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Abstract—A solution to the problem of redistributing agents between groups based on simulating a form of social parasitism in ants known as slave-making is considered. To provide a comprehensive solution, the problem is integrated with a method of orientation based on visual landmarks and a compass, including route memorization and return. The models and mechanisms used are described. It is shown that even technical problems, such as following a leader, can be solved using bioinspired mechanisms.

Keywords: collective robotics, social behavior models, group movement, following the leader, ant slave-making, aggressive behavior, foraging task

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INTRODUCTION

In the field of collective robotics (CR), approaches that predominantly develop separate models (methods, algorithms) to solve various problems are used. These models are then either proven to be optimal under specific conditions or demonstrated to be superior to existing methods and algorithms. This approach not only results in high labor intensity for solving even typical or similar CR problems but also means that these "monolithic" solutions prevent the integration of existing models and methods.

An alternative to this approach is the development of basic behavior models that underlie complex behavior, both individual and social. This is the essence of the paradigm of social behavior models (SBMs) [12]. The SBM approach is based on the study of the behavior of social insects, primarily ants. In nature, a group (family) of ants effectively solves the problems they face using a rather limited set of mechanisms, skills, and behavior models. They solve these problems not optimally but rationally and are highly adaptable to changing environmental conditions. Comprehensive simulation of such behavior in collective robotics will make it possible to solve various robot group control problems without developing separate algorithms for each task. Therefore, the application of a bioinspired SBM-based approach is a promising area.

The essence of the methodology for applying SBMs to practical problems is as follows. First, a real-world problem is posed, for which a "natural analogue" is sought. This analogue is viewed as complex behavior or a set of behavioral procedures. Next, a set of basic behavioral mechanisms is developed as the basis for implementing the desired behavioral phenomenon.

In this paper, the application of this approach is described using the example of solving the problem of redistributing agents (robots) between groups. Such a problem may arise, for example, if some of the robots in a group come out of action. In the literature, an approach that involves redistributing tasks between groups rather than participants is most often described [20]. When changing the composition of a group, methods based on games or auctions are typically used [2]. During the auction, the capabilities of robots (groups of robots) and the characteristics of the tasks are compared, and, if necessary, dynamic redistribution of group members occurs. For example, in [10], an algorithm is proposed in which the group leader evaluates at each step whether the capabilities of the group members are sufficient to solve the assigned task. If not, it contacts the leaders of neighboring groups to conduct an auction to attract members of other groups to its group. In general, the formation of robot groups is often carried out by distributing tasks between groups and is decided jointly [25]. Thus, existing algorithms for changing group composition are based on voting and imply data exchange and coordination of results.

Some studies dealing with the organization of robot groups are based on biologically inspired models. For example, work [5] examines the problem of distributing tasks among group members. The solution includes a stimulus–response model and a set of simple selection rules based on the division of labor in social insects. However, the problem being solved is

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purely theoretical, as it does not consider any factors other than the response thresholds at which the robot selects a task and the stimulus intensity.

The purpose of this study is to implement complex agent behavior using previously established models, methods, and mechanisms. The problem being solved is the mobilization by agents of one group agents from other groups to redistribute labor resources. From here on, the subject of behavior will be referred to using near-synonymous terms: *agent, animat* (an agent simulating the behavior of a living organism), and *robot*. This is determined by the aspect of interest at the given moment: an abstract model entity (agent); behavior analogous to animal behavior (animat); or a hardware implementation (robot).

1. SOLUTION TO THE PROBLEM OF ANIMAT REDISTRIBUTION

The SBM-based approach focuses on the formation of stable groups of animats that must function together over an extended period. In addition to such a permanent entity as an ant colony, a constant individual composition of worker groups has been observed in some ant species. Such a group carries out joint activities for an extended period, up to several days and even weeks [24]. Redistribution of individuals is possible both between worker groups within a single colony and between colonies. We will consider the latter option.

Some ant species employ a mechanism for redistributing individuals between colonies known as slave-making. This form of social parasitism involves plundering the broods of other colonies and breeding the captured individuals in the enslaver's nest [3]. Subsequently, the captured individuals (called slaves) are integrated into the activities of the slave-owning families.

The mechanism of animat redistribution between groups based on slave-making was examined in [17]. It describes both the key features of the slave-making phenomenon and the behavior models and algorithms by which this mechanism can be implemented in animat groups. Individuals from a foreign colony (another group) can be considered a resource, which is obtained through foraging. In search of a resource, a scout ant explores its sector of territory around the nest. It then returns to the nest and, using special signals, mobilizes other ants—the so-called passive foragers—to join the expedition: mechanisms of cohesion (the desire to stick together) and dominance/subordination are at work here. Having mobilized the foragers, the scouts lead them to the foreign nest, where two mechanisms come into play: aggression and imitative behavior. More aggressive individuals (scouts and foragers) evoke a submissive response in less aggressive individuals from the other nest. Young individuals are less aggressive: individual aggressiveness increases with age, as is known for all social insects and has been experimentally demonstrated for ants ([8, 27]). Young individuals adopt a submissive posture—folding themselves into a "suitcase-"shaped form and resembling pupae. Foragers imitate scouts, which perceive strangers as a resource and therefore also transport them to their nest.

The mechanism that triggers this procedure is unimportant in this case. However, one possibility could be a natural increase in aggression (and, consequently, activity) as the supply of resources into the nest declines. Then, scouts begin to search more actively, foragers respond more often to the call to follow the scouts, and their increased aggression facilitates the successful capture of alien individuals, perceived as a resource, during the raid.

During movement, first scouts and then foragers must memorize their route to be able to return. For this purpose, a mechanism for orientation using visual landmarks and a compass was developed, similar to that found in many ant species. During movement, the animat memorizes its route using visual landmarks, taking into account compass readings and the time component. The path is viewed as a sequence of scenes formed by landmarks, and the routes of both the scout and forager animats are defined as transitions from landmark to landmark. The animat world contains a "base," stationary objects (landmarks), and certain target objects—a "resource"—that must be transferred to the "base" (Fig. 1).

The created animat behavior model operates exclusively in relative categories, without reference to absolute physical quantities. To achieve this, the environment is virtually divided into cells, the size of which is determined by the robot's characteristic linear size (model or real). Ordinal scales and rules for converting real values into conventional units (cells) are introduced for the concepts of "distance" and "direction." The route is memorized "approximately," and upon repeating it, the animat does not attempt to precisely repeat it.

Let there be a set Ω of N objects x_n recognized by the animat in its world: $\Omega = \{x_n\}$, $n = 1, \ldots, N$. By *landmark Q* we mean one or more objects that form a compact group, i.e., located close to each other:

$$\begin{gathered} Q = \{x_i\}, \{x_i\} \subset \Omega\colon \forall x_k \in Q \\ \exists x_m\colon x_m \in Q, \rho(x_k, x_m) \le \Delta. \end{gathered} \tag{1.1}$$

Here, ρ is the distance between objects (e.g., Euclidean), and Δ is the upper limit of the "very close" range. The presence of identical landmarks necessitates the recognition of scenes rather than individual landmarks or objects. A scene is a collection of visible landmarks, the spatial relationships between them, compass directions, and the temporal component. The scene determines the animat's behavior and changes in its state.

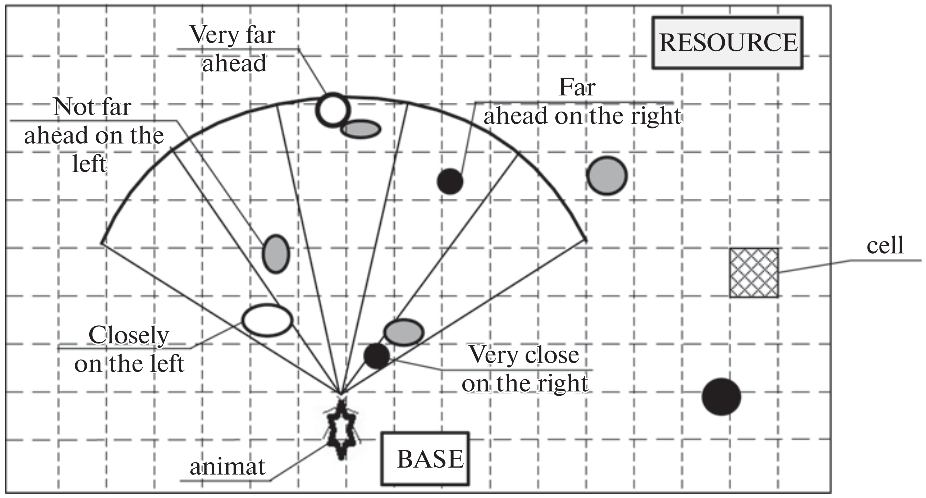

Fig. 1. Animat's world representation: field of view, direction, distance.

The route is described as a sequence of scenes $\Omega = \{S_j\}, j = 1, ..., L_p$, where L_p is the number of scenes of the route. Each scene S_j consists of a set of landmarks $\{O_i^j\}$ (1.1), one of which is in the focus of attention and is the reference point (all actions are performed in relation to it). In turn, each landmark O_i^j consists of a set of observable objects with their characteristics (context) W: $O_i^j = \{W_k\}$

$$W_k = \{Id, X, \{(dir, dist)\}, Compass, Timer\}, \quad (1.2)$$

where *Id* is object identifier (for example, ArUco marker); *X* is reference landmark indicator (direction of traversal of the landmark); $\{(dir_i, dist_i)\}$ are a set of pairs storing the direction and distance to the left boundary, the center of the object, and the right boundary, respectively; *Compass* is the value of the compass sensor; *Timer* is the numbers of ticks at the beginning and end of the path segment.

Scene matching is performed using pseudophysical (spatial) logic rules [22] and context-sensitive landmark comparison (see [14] for more detail). To return to the base, the route description Ψ was transformed into a reverse route Ψ'. The reverse route consists of the same scenes as the forward route but in reverse order [15]. For the forward route, the end point is the resource being sought, while for the reverse route, it is the "base." Landmarks in each scene are mirrored from left to right, and the direction of movement is reversed. Short scenes are skipped, increasing the stability of the animat (and the robot) along the route. The maximum duration of short scenes was determined experimentally at 50 model time cycles. The effectiveness of this method is confirmed by experiments on real robots, which are described in [16].

The orientation method was integrated with the mechanism for capturing animats (agents) from another group to redistribute agents between groups.

2. THE PROBLEM OF FOLLOWING THE LEADER

During the integration of the above-described mechanisms, some seemingly purely technical difficulties arose in organizing group (swarm) movement. These were related to the coordinated movement of the group (following the leader): the group often failed to move in a stable formation. In a simple case, swarm movement, from the SBM perspective, is organized as follows. Animat A, which does not see anyone stronger (more aggressive) around it, implements its behavioral procedure: in this case, it moves in the desired direction. If animat B, which is less strong and aggressive, is next to animat A, then animat B follows animat A, recognizing it as its leader.

Clearly, such a straightforward strategy does not effectively solve the problem of swarm movement. First, if the leader is geometrically located within the group, and all followers strive to approach the leader, they will surround it from all sides, and it will be unable to move. Second, if it moves at the head of the group, the followers may lose sight of it, and the group will disintegrate. Thus, the thesis that the only distinguishing feature of a leader is disobedience to the swarm law proves untenable in a number of cases [11]. A leader does not simply perform a task, such as going somewhere. It must organize the group and control its movement; otherwise, the group will simply disintegrate. In other words, the leader must implement a specific behavioral procedure.

There are many models of group movement of agents, both at the micro- and macrolevels. For example, in [7], the rules of swarm movement are based on a spring and shock-absorber model. The “spring” component of the model determines the attraction of individuals to the leader, and the “shock-absorber” component determines their repulsion from the leader. In fact, this model is very similar to the Reynolds model of swarm behavior. Macrolevel models are usually based on the analogy of the movement of groups of agents with the behavior of particles (hydro- and gas dynamics) [1].

For agent-based modeling, a set of individual rules of behavior is proposed [21], cellular automata models are often used ([18, 26]), and models with a virtual leader are considered [19]. Of greater interest to us is article [6], which proposes a stochastic model of the random movement of a small group of individuals. According to the authors, this model considers the social behavior of individuals in a group. The model reduces the likelihood of their close physical contact and collisions with internal obstacles. The equations of motion of individuals are written as a system of ordinary stochastic differential equations. The direction and speed of the desired movement of an individual are described by a time-structured random process. Social behavior and the interaction of individuals with obstacles are modeled by an effective potential. Thus, the inclusion of social behavior in this work can only be considered conditionally. Instead of models of social behavior, this work simulates a separate phenomenon using purely mathematical methods.

In fact, such multiparameter models are not applicable within the SBM framework. We do not address the problem of calculating optimal trajectories, minimizing conflicts, etc. Agents are guided exclusively by primitive rules of motion, similar to those defined in Reynolds’s classical work [23]: speed coordination, avoiding collisions with neighbors, and attraction to neighbors. We are interested only in qualitative confirmation of the necessity of similar rules in model individuals. First, let us consider this issue from a formal perspective. Since we rely on the Reynolds rules when describing the nature of agent motion, a formal, qualitative justification for the inevitable deviations in formation movement might look as follows.

The speed of a group’s movement is always slower than that of an individual agent (the leader). This is due to factors such as the need to (1) orient oneself towards the leader and (2) prevent potential collisions, which requires additional time.

Let us assume that we know the following:

• agent’s movement speed $V_{\max}$: for the sake of simplicity, $V_{\max}$ is the same for all;

• $T_{a/d}$, the time the agent spends for braking and accelerating: we will assume that it starts off and accelerates to $V_{\max}$, as well as brakes to a complete stop in the same amount of time;

• time T_{ins} spent for inspection conducted by the leader;

• $R_{\max}$, the distance at which agents can see each other;

• the distance $R_{\min}$, at which agents must maintain contact with each other to prevent collisions ($R_{\min} \ll R_{\max}$).

It is necessary to determine such a law of movement of the leader that will ensure the maximum speed of movement of the entire group.

Let the leader move along a straight route at maximum speed ($V_L = V_{\max}$). The resulting speed of the group V_{gr} is lower than the speed of the leader’s movement V_L because of the following. When agents approach one another for a distance less than $R_{\min}$, their collision avoidance routine is activated: if an agent sees another agent ahead, it must stop and move backward; if it sees another agent to the side, it must turn in the opposite direction. After this, it reverts to the follow-the-leader routine and begins moving forward (or turning back). Consequently, the path it travels will be longer. Let us estimate the time it takes the agents to travel this path. Let $T_{\min}$ be the minimum time to travel a route of length L at a speed $V_{\max}$ when moving in a straight line: $T_{\min} = L/V_{\max}$.

Then the actual time spent by the agent T_{real} can be assessed as follows:

$$T_{real} \approx \left(T_{\min} + T_{turn} + T_{a/d} + \frac{\Delta L}{V_{\max}}\right) > T_{\min}. \tag{2.1}$$

Here, T_{turn} is the time it takes the agent to make a turn; $T_{a/d}$ is the time the agent spends for braking and accelerating; ΔL is the additional distance an agent must travel due to maneuvers. In reality, the route is not straight due to obstacles, but all group members navigate around obstacles, and the speed of completing the route is further reduced.

Since the group, as shown above, has the resulting speed $V_{gr} = (L + \Delta L)/T_{real}$ (2.1) that is lower than the speed of the leader V_L, the most efficient way to coordinate these speeds is to introduce pauses in the leader’s movement. Pauses are determined by two parameters: their frequency F and their duration T_{stop}. It is necessary to determine the frequency F of stops and the duration of these stops for the leader T_{stop} under the following conditions:

(1) the leader should not move away from the group for more than $R_{\max}$;

(2) the follower closest to the leader must not approach it for less than $R_{\min}$.

Time expenditure on inspection T_{ins} consists of:

$$T_{ins} = 2T_{a/d} + T_{turn} + T_{stop},$$

where $T_{a/d}$ is time of braking and acceleration; T_{turn} is time to turn around to see the followers ($T_{turn} = 0$ if the agent has an omnidirectional vision system); T_{stop} is stop duration.

To solve the problem of group connectivity control, one can do the following.

(A) Specify the frequency of stops F and change T_{stop} depending on the distance to the nearest follower: if the follower is near, it is necessary to reduce T_{stop}; if it is far away, it is necessary to increase T_{stop}.

(B) Record the stop time T_{stop} and change the frequency depending on the distance.

In the simulation experiments described in Section 3, option A was used. The stopping frequency was determined from the following relationship. The leader moves away from the followers at a speed ($V_{max} - V_{gr}$). In this case, the distance between the leader and the closest follower must remain within [R_{min}, R_{max}] to remain within the field of view. Then, the time after which the leader must stop and look around must be within the following limits:

$$\frac{R_{min}}{V_{max} - V_{gr}} + T_{a/d} < F < \frac{R_{max}}{V_{max} - V_{gr}} - T_{a/d}. \quad (2.2)$$

Similar effects of a reduced speed for a leader guiding a group are observed in nature. For example, in a school of fish, the individual swimming at the front of the school does not move at maximum speed: it must overcome greater environmental resistance. While in fish this occurs due to the laws of hydrodynamics, in social insects it is part of social behavior. In ants, this phenomenon is well described during tandem movement, when a scout leader guides a single forager follower. For the follower ant to recognize and remember landmarks, the leader must move much more slowly, make frequent stops, and turn around [4]. In this way, the leader controls its follower within the framework of social behavior. The speed of tandem movement is much lower than that of an individual ant. For example, in *Temnothorax albipennis* ants, a tandem moves approximately 4 times slower than a single forager [9]. In the experiments to estimate F (2.2), it was assumed that $V_{gr} = 0.5V_{max}$, and the middle of the obtained interval was taken as the F value.

Thus, in solving the leader-following problem, it turned out that ensuring group cohesion is not a purely technical issue. It can be solved within a bioinspired approach by modifying the leader's behavior, although superficially this appears to be a technical feat: the animat (robot) must periodically stop and assess the distance to its followers if it "considers itself the leader" and leads the group.

3. SIMULATION EXPERIMENTS

Simulation modeling was conducted using the Kvorum multiagent modeling system [13]. Two groups of animats, A and B, were created for the experiments. One of them, group A, needed new members. To organize joint actions, the animats must recognize each other and distinguish between friends and foes. Each animat is assigned a number—an identifier, *Id*. This number is generated automatically at the beginning of the experiment. The identifier values are divided into ranges—one per group—and the *Id* value belonging to a range determines the animat's membership in the group. Animats continuously generate a signal the value of which is equal to *Id*. By perceiving this signal, they can understand whether the individual in front of them is a friend or a foe. Moreover, the *Id* value is interpreted as the animat's rank and depends on its internal state (level of aggression).

In the experiment, a scout from group A initially left its "base" to search for a resource, which was the "base" of group B. The scout then returned and emitted a signal equal to its *Id*. The foragers of group A, having perceived this signal, determined that it was a signal from a higher-ranking agent within the same group. The reaction to this signal was to follow the leader. The scout then retraced the memorized route, monitoring the foragers following it during periodic stops. Having reached the "base" of group B, the scout and the foragers attempted to capture members of this group. The following subordination mechanism was used for this [17]. An active forager perceives both food and a passive ant of a different species as a resource. However, it cannot change another individual and transfer it from an active state to a passive one: this must be the initiative of the one being subordinated. Therefore, when encountering an aggressor, the weaker ant (less aggressive, younger) adopts a submissive posture. This signifies a change in the animat's internal state, leading to a decrease in its rank (its *Id*) and the signal it generates. This signal transforms the weaker animat into a resource, attractive to the forager. The forager must then deliver this "resource" to its "base." In the experiments, the forager simply led the captured animat to its "base," acting as the leader in a tandem.

An example of running the simulation program is shown in Fig. 2a (the rectangles are landmarks, and the hexagons are group "bases"). This example shows that not all animats in group A followed the leader (Fig. 2b), and not all reached the target: one lagged behind and returned to the "base" (Fig. 2c).

Presenting statistical data on experimental results and evaluating them is of little use. Modeling, depending on the model parameter values, can yield any results: from minimal susceptibility of animats to "enslavement" to the complete transition of all animats to a single group. However, these experiments had a different purpose. They were intended to confirm the feasibility of integration and the viability of the developed models and algorithms. This goal was achieved.

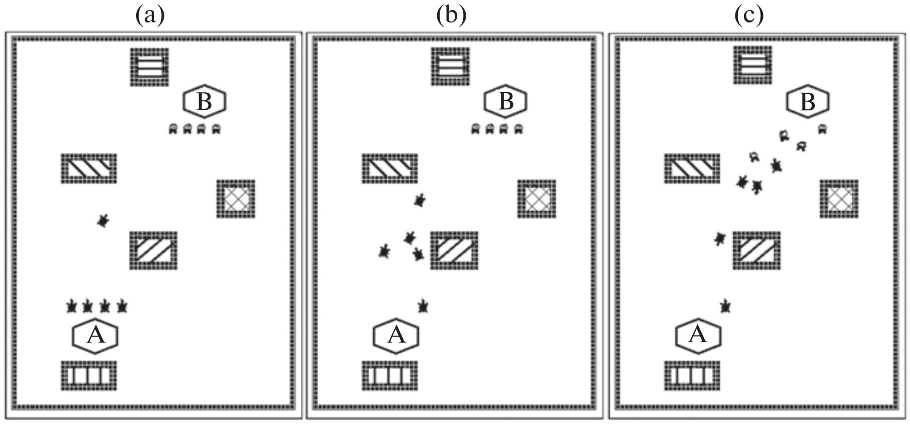

Fig. 2. Simulation example: (a) a scout searches, (b) a scout leads a group of foragers, (c) animats of another group follow the foragers.

CONCLUSIONS

A mechanism was developed and implemented that allows for a relatively natural redistribution of agents (robots) among groups. It is based on simple rules of individual behavior, similar to those used by social insects, and does not require centralized control or coordination. Implementing this mechanism required integrating the orientation and navigation method with mechanisms of aggressive behavior and submission/dominance. Furthermore, it was demonstrated that even the task of ensuring group cohesion during leader following can be solved within a bioinspired approach by modifying the leader's behavior.

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CONFLICT OF INTEREST

The author of this work declares that she has no conflicts of interest.

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