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The appearance of «intelligence» in self-propelled bots

Relevance. Nowadays, the study of the behavior and properties of active matter, which corresponds to the collective behavior of self-moving elements, is very promising field of research. Active matter is widespread in nature and is used in various modern technologies.
Objective. To study the collective behavior of mobile bots in a simple maze and to determine the distinctive trends in the single bots exiting from the maze as their number increases.
Research methods. To perform the research, mobile bots have been created and their behavior in the maze has been analyzed. Their positions and interactions were recorded on a video, and processed to obtain the necessary data.
Results. The research revealed the existence of an optimal number of bots in the maze for which the average time to exit the maze is minimal. The determined dependence of the probability of bots leaving the maze is non-monotonic, and there is a number of bots for which this probability is minimal. It has been determined that with 12 bots in the maze, both the average exit time and the exit probability are minimal. Thus, with this number of bots, a small number of bots quickly exit the maze. A quantitative measure of bot intelligence, the intelligence coefficient, is proposed. There exists an optimal number of bots that maximizes the measure of «intelligence» concerning the task of exiting from the maze. Both a decrease and an increase in the number of bots lead to a reduction in the «intelligence» of the bot collective. The measure of the «intelligence» of a bot collective surpasses that of an individual bot.
Conclusions. In this work, we have considered the groups of self-moving bots exiting the maze and the typical quantitative characteristics that allowed us to determine the main dependencies of their behavior.

Keywords: *active matter systems, clustering, research, observation, visualization of results, arenas, bots, research application.*

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1. Introduction

Recently, there has been considerable interest in the study of active matter. Active matter is understood as sets of self-moving elements or bots [1]. These systems exhibit special behavior that distinguishes them from ordinary systems of physical particles. The study of active matter began with the study of swarming behavior in fish [2]. In a more recent and significant work [3], the motion of bird-like objects, bots, has been modeled. Over time, both experimental and theoretical studies have deepened the understanding of behavioral mechanisms of various biological systems, as discussed in the review [4]. Obviously, artificial swarms of self-propelled bots, which are also actively investigated (see, e.g., [5]), belong to the category of active matter. In addition, such studies contribute to the field of cybernetics. An example is the study of the interaction of abstract automata or other computational models. These studies are closely related to biological studies of animal behavior. The main goal of these studies has been to understand the behavior of different animals and their problem-solving abilities, which is akin to studying their "intellectual" abilities. In a sense, this direction is equally relevant to the creation of artificial systems with purposeful behavior.

The interaction of abstract automata, without loss of generality, can be regarded as the problem of guiding a finite automaton through a maze. One of the earliest works in this area was Shannon's study [6], which explored a maze-solving problem using a mouse automaton. This idea for this research emerged from existing and highly advanced biological studies of the behavior of various animals and creatures in mazes, with mice being classical subjects.

Studies on the behavior of automata in mazes have been further developed in works [7, 8], where questions about the existence of a finite automaton capable of traversing all possible mazes were formulated. It was quickly proven that such finite automaton does not exists [9, 10]. Further research has focused on determining which mazes could be traversed by a single finite automaton [7, 8, 11, 12], and some generalizations of automata, such as those with external memory, have also been considered (see, e.g., [13]).

In this work, we examine the behavior of self-propelled bots in a simple labyrinth, inspired by the framework proposed in [14] where the exit of conventional elements from the maze has been studied in detail. For our research, we constructed self-propelled bots with micro-vibration motors. Subsequent experiments to navigate the bots through the maze allowed us to identify key dependencies that characterize the behavior of bots when exiting the maze. We introduced the concept of "intelligence coefficient" as the ratio of the average exit time of a single bot to the average exit time of all bots from the maze. Our results indicate the existence of a certain number of bots that optimally solve the problem of exiting the maze in minimum time.

2. Self-propelled bots

For the experiments, a self-propelled bot with a vibration motor has been developed (Fig. 2.1). Unlike the previously used variants [15, 16], where the motion of the bots was stimulated by vibrations of the external surface, each bot was equipped with a vibration motor and power source. Such a design required multi-parameter optimization of the power source parameters and placement, as well as the optimization of the vibration motor, to achieve stable mobility of the bots. The advantages of this design include the autonomy of each bot and its relatively high independence of.

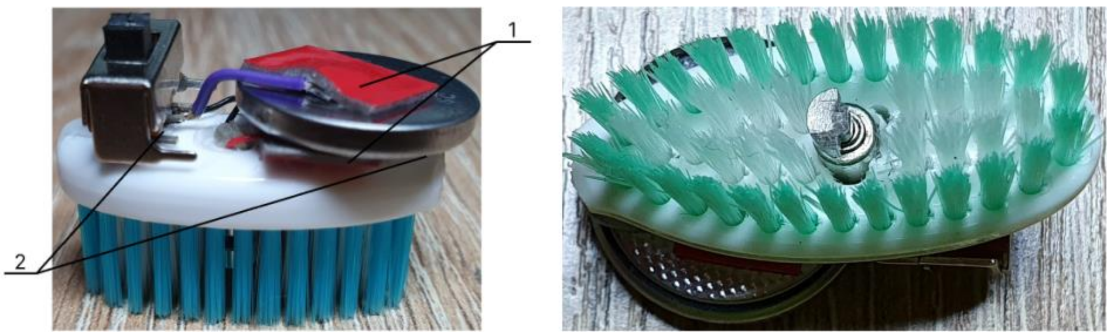

Fig. 2.1 On the left is the overall view of the bot: 1 – updated adhesive strip; 2 – adhesive layer for fixation, switch, and wire connections. On the right the motor placement is presented

A microvibration motor with the following characteristics has been chosen to propel the bot:
- Motor length (total): 8 (11) mm;
- Wire length: 10 mm;
- Weight: 0.6 g;
- Voltage: 1.5 V, Current: 15 mA;
- Voltage: 3 V, Current: 23 mA.

The bot's power source is a lithium battery with the following characteristics:

- Model: CR2032;
- Voltage: 3 V;
- Battery capacity, mAh: 220;
- Weight: 2.9 g.

Due to the shifting center of gravity, the elliptical platform with bristles can move relatively rectilinearly on a flat surface. After considering several options, a prototype in which the motor was located inside the body of the bot allowing maximum transmission of vibration impulses to the locomotive part of the bot has been selected (Fig. 2.1). In order not to interfere with the rotational motion of the motor, the bristles around the motor location have been removed.

Fig. 2.1 shows the location of the motor inside the bot body. The isolated bristle at the motor location can be seen, and it is clear that it does not interfere with the rotational motion of the microvibration motor. The characteristic dimensions of the bot are $1{,}8 \times 3{,}5\ cm^2$ with a height of 2.5 cm.

These last improvements completed the bot design. After that, replication of the bots began so that the total number of bots would be at least twenty-one units (fifteen main bots and a minimum of five spare bots in case of malfunction). Additional bots were necessary because for the proposed modification, it is easier to replace a bot than, to replace a battery, for example.

After launching the bots, a characteristic interaction characterized as elastic collision was observed during each experiment. Upon collision, the bots formed clusters, demonstrating signs of system self-organization. However, as the study showed, the bot clusters were quite dynamic and constantly changed their positions in the constructed arenas, as well as the number of agents (bots) in them.

3. Experimental observations

After creating the necessary number of bots, a simple maze has been constructed (Fig. 3.1). The outer boundary of the maze has been made of wood, and the internal intersections from foam. The glass surface has been used for the bots to move on. The dimensions of the maze that need to be characterized are the area of the wooden boundary, the structural elements of the maze, and the size of the maze exit. Therefore, the area of the maze outline is $S_{outline} = 1046.3467\ cm^2$; the area of the T-shaped and rectangular elements is $S_{T-element} = 77.4\ cm^2$ and $S_{rectangle} = 19.6\ cm^2$, respectively. According to the defined dimensions, the width of the maze exit was determined to be 9.5 cm.

In each experiment, an initial set of bots was placed in a relatively small area measuring $8.2 \times 11.5\ cm^2$, and the initial movement directions were random. It is worth noting that the bots started from containers located in the middle of the maze (Fig. 3.1).

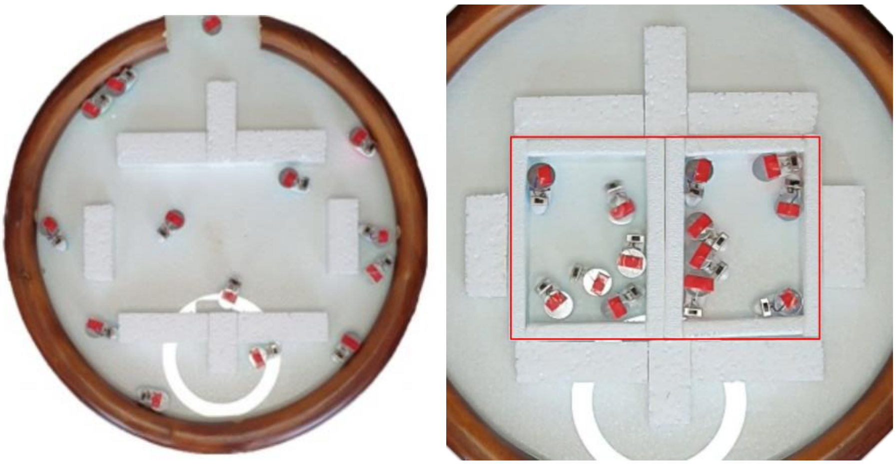

Fig. 3.1 On the left is a general view of the maze arena. On the right is a demonstration of containers for bots

The behavior of the bots has been recorded on video. Quantitative and qualitative details of the bot's behavior in the maze were determined from the video recordings. Three observations were conducted for each set of bots (2 – 15).

4. Experimental results

Observations over groups of bots allowed us to obtain data on the dynamics of bots exiting the maze.

Starting from one bot, the average time of bots exiting the maze was determined. This time was calculated in accordance with the relation (4.1):

$$\langle t \rangle_N = \frac{1}{n} \sum_{i=1}^{n} t_i \tag{4.1}$$

where t_i is the exit time of the i-th bot from the labyrinth;
N is the initial number of bots in the labyrinth;
$n < N$ is the number of bots from N that found the labyrinth exit.

Experimental data for t_i have been determined by timing video recordings. It is important to note that averaging was performed only for bots that exited the labyrinth. Otherwise, the exit time would depend on the waiting time, which is not acceptable. After conducting several experiments (three in particular), these average values were additionally averaged over realizations. Mean square errors for these data were also determined. The results for the average exit time of bots depending on the number of bots N are shown in Fig. 4.1.

In Fig. 4.1, the dots represent experimental data, connected by straight lines for clarity. Mean square errors are indicated by vertical bars.

Determining the average exit time for a single bot posed a certain problem. The reason is that a solitary bot does not always find the exit from the labyrinth. To determine $\langle t \rangle_1$, additional experiments were conducted (20 observations), in which the exit time of a single bot from the labyrinth was recorded when there were no other bots in the labyrinth. Only three observations from the ensemble were used because it took 20 experiments to record the bot's exit within 40 seconds for three of them. Thus, the probability of a solitary bot exiting the labyrinth is quite small $p_1 = 3/20$. It should be noted that for a solitary bot, exiting the labyrinth is a challenging task.

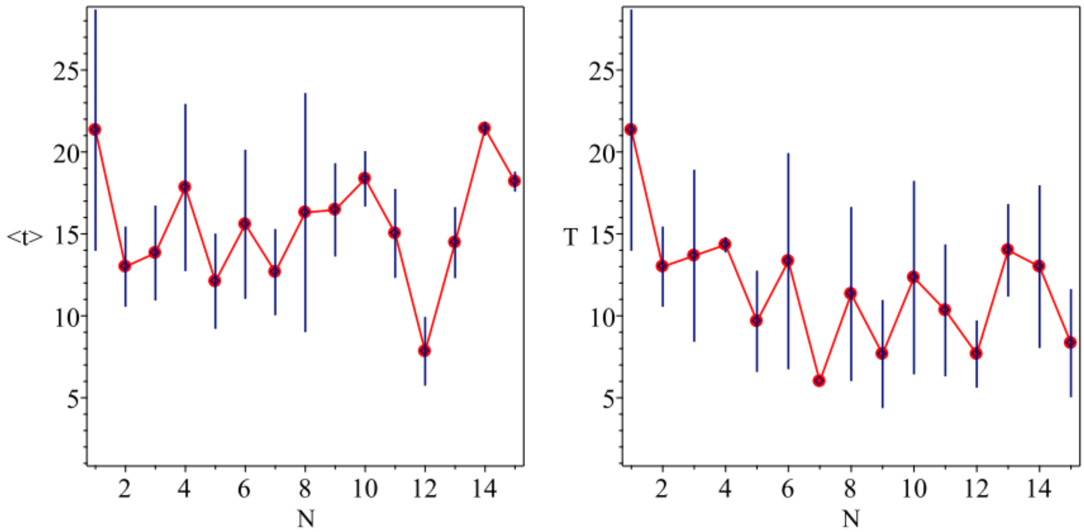

Fig. 4.1 On the left, the dependence of the average exit time of a bot from the labyrinth on the number of bots in it is presented. On the right, the average exit time of the first bot from the labyrinth and the data errors are shown as well, depending on the group size

It is easy to notice the presence of a certain number of bots (12), for which the average exit time from the labyrinth is minimal.

It is interesting to consider the average exit time of the first bot as an additional characteristic. This dependence on the number of bots in the group is shown in Fig. 4.1 on the right. It is easy to notice that this dependence does not have a pronounced minimum. The minimum value is achieved with a different number of bots (7) in the group. Errors for these data also noticeably increase. Thus, the exit time of the first bot weakly depended on the number of bots in the group. The solitary bot is an exception, as its exit time is significantly longer. Therefore, the average exit time of all bots from the labyrinth should be used as a value sensitive to the number of bots in the group.

Another important characteristic of the behavior of groups of bots in the maze is the probability of bots leaving the maze. We define it as the ratio of the number of bots that left the maze to the total number of bots. Based on the data obtained, we determined the probability of a bot exiting the maze as a function of the initial number of bots in the maze. This dependence presented on the Fig. 4.2.

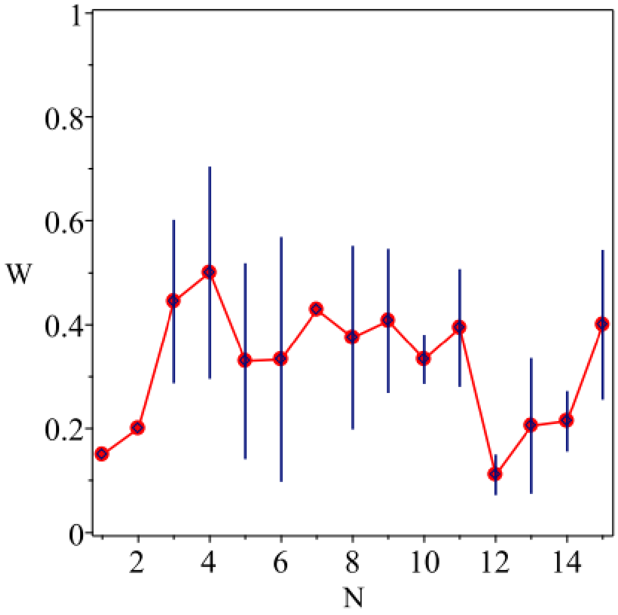

Fig. 4.2 Probability of a bot belonging to a group of N bots to exit the labyrinth

It is easy to see that a solitary bot has a low probability of exiting. It should be noted that its probability was determined differently for understandable reasons. The probability was taken as the relative frequency of favorable events, i.e., the number of experiments in which the solitary bot exited the labyrinth, to the total number of experiments. From Fig. 4.2, it can be deduced that a group of bots more efficiently solves the task of exiting the labyrinth than a solitary bot. It is important to note that there is a probability minimum when the number of bots is 12, the same number for which the average time for bots to exit also has a minimum. In fact, this means that bots exit quickly but with low probability, or a relatively small fraction of the group. In a sense, this can be interpreted as a kind of "altruism" - the group ensures that a small part of the group exits the maze quickly.

Let's return to the discussion of the overall task of finding labyrinth exit. In biology, and beyond, this task has often been employed to assess the ability of a subject to solve the maze exit problem. Comparing the performance of different entities in this task allows conclusions to be drawn about their abilities to address this challenge, essentially making insights about their «intellectual» capabilities. In this context, «intellect» is generally understood as the «ability to solve problems». While there is no universally accepted definition of intelligence, most definitions focus on human intelligence [17]. However, for the broadest working definition, we will rely on the one provided above. While this definition has obvious limitations, it serves well as a characterization of the abilities of animals, humans, and swarm intelligence as well.

Based on this, it is natural to introduce a quantitative measure to determine intelligence based on how the labyrinth exit task is solved. If a collective solves the exit task in less time than another, it is deemed more «intellectual». It is logical to measure intelligence in a swarm relative to its solitary representative. Therefore, we will use the ratio of the average exit time for a solitary bot to the average exit time for the swarm as a coefficient of «intelligence» (Fig. 4.2):

$$I_N = \frac{\langle t \rangle_1}{\langle t \rangle_N} \tag{4.2}$$

where $\langle t \rangle_1$ – average exit time for an individual bot from the labyrinth;

$\langle t \rangle_N$ – average exit time for a system of N bots.

It could be seen that, if the average exit time for a swarm is less than the exit time for an individual bot, then the intelligence coefficient will exceed one. For a solitary bot, its value equals one by definition.

The dependence of the «intelligence» coefficient on the number of bots in the swarm is derived from the experimental data and presented on Fig. 4.3. It is noticeable that the intelligence coefficient for swarms exceeds its value for a solitary bot within the margin of error. It is interesting to note the presence of a clear maximum value $I_{12} \approx 2.7$ when there are 12 bots in the swarm. Understandably, such a dependency corresponds to the behavior of bots in this particular labyrinth. Expectations are that changing the labyrinth may alter this relationship. In a sense, this implies a change in the task, and consequently, the intellectual abilities of the swarm may differ. However, general properties, such as the presence of a maximum, are likely to remain, albeit in a different location. This could be interpreted as the existence of an optimal number of bots in a swarm that solves a specific task most efficiently. Increasing the number of bots sharply decreases the intelligence coefficient. One possible reason for this is the formation of clusters or grouped bots that block the exit from the labyrinth.

Understandably, expanding the scope of tasks, i.e., including any labyrinths from which bots can exit, should cause this dependence to lose the presence of a maximum. This is inferred from the existence of a maximum for a specific labyrinth at a certain number of bots in the swarm. Accordingly, for several labyrinths, one should expect the presence of multiple maxima. Averaging over implementations will reduce their amplitude. As the number of labyrinths increases, there will always be one that can be successfully navigated with a larger number of bots in the swarm. It is possible to hypothesize that the intelligence coefficient concerning the traversal of any labyrinth will increase with an increase in the number of bots in the swarm.

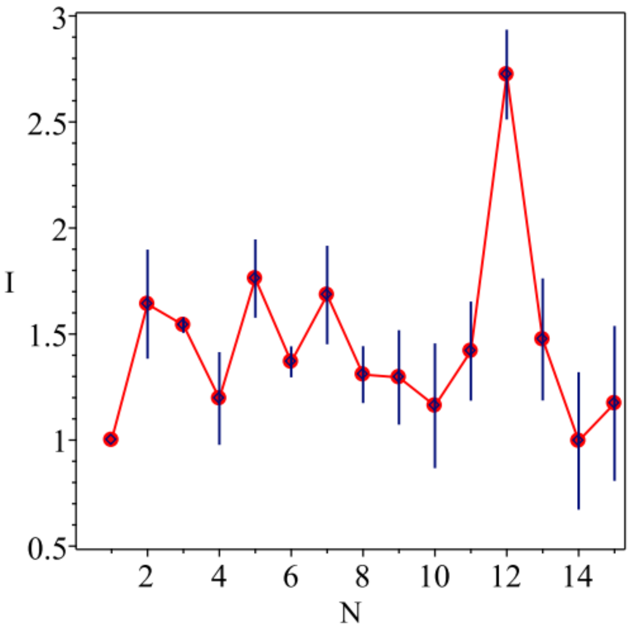

Fig. 4.3 Dependence of the intelligence coefficient on the number of bots in the swarm

5. Conclusions

In this study, the behavior of elementary bots in a labyrinth has been explored. Each self-propelled bot lacks specialized information processing systems and interacts solely through collisions with other bots, potentially leading to a statistical alignment of their behavior, a phenomenon that warrants further investigation. The research revealed the influence of the number of bots on the average exit time from the labyrinth. A distinctive dependence of the average exit time on the number of bots was identified (Fig. 4.1). The existence of an optimal number of bots in the labyrinth, resulting in the minimum average exit time, was determined. A non-monotonic dependence of the probability of bots exiting the labyrinth was obtained, with a specific number of bots minimizing this probability (Fig. 4.2). It was found that with 12 bots in the labyrinth, both the average exit time and the exit probability are minimal, signifying a quicker exit for a smaller portion of bots.

A quantitative measure of the «intelligence» of bots in solving the task of labyrinth exit was proposed. Naturally, the intelligence coefficient utilizes the ratio of the average exit time for a solitary bot to the average exit time for the swarm of bots. An optimal number of bots was identified, maximizing the «intelligence» concerning the task of labyrinth exit performance (Fig. 4.3). Both a decrease and an increase in the number of bots result in a decrease in the swarm's «intelligence». The intelligence measure of the swarm surpasses that of the solitary bot, accounting for data errors.

It is essential to note that, at first glance, characterizing the efficiency of solving the labyrinth exit task by the fraction of bots that successfully exit may seem plausible. However, such a definition has significant drawbacks. For instance, if a labyrinth is chosen where a solitary bot always finds the exit, its exit success rate would be 1, a priori higher than the rate for other swarms. Consequently, such a characteristic does not align with the existence of swarm intelligence, observed and thus cannot be deemed acceptable.

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Виникнення «інтелекту» у саморухомих ботів

Актуальність. Наразі є дуже перспективним розвиток сучасного напрямку досліджень поведінки та властивостей активної матерії, яка відповідає колективній поведінці саморухомих складових. Така активна матерія широко поширена в природі та використовується у різних сучасних технологіях.
Мета. Провести дослідження колективної поведінки рухомих ботів у простому лабіринті та визначити характерні закономірності у виході цих частинок з лабіринту зі збільшення їх кількості.
Методи дослідження. Для виконання досліджень були створені рухомі боти та проведені експерименти по їх поведінці в лабіринті. Фіксація їх положень та взаємодії фіксувались відео записом, обробка якого дозволила отримати необхідні дані.
Результати. Виявлено існування оптимальної кількості ботів у лабіринті, для яких середній час виходу з лабіринту мінімальний. Визначена залежність ймовірності виходу ботів з лабіринту теж має не монотонний характер та існує кількість ботів за якої ця імовірність мінімальна. Визначено, що при наявних дванадцятьох ботах у лабіринті середній час виходу мінімальний, як і ймовірність виходу. Таким чином, при цій кількості, з лабіринту швидко виходить менша частина ботів. Запропоновано кількісну міру інтелектуальності ботів — коефіцієнт інтелекту. Існує оптимальна кількість ботів, яка має максимальну міру «інтелекту» по відношенню до задачі виходу ботів з лабіринту. Зменшення, як і збільшення кількості ботів веде до зменшення «інтелекту» колективу ботів. Міра «інтелекту» колективу ботів перевищує «інтелект» одного бота.
Висновки. В роботі було розглянуто вихід зграй саморухомих ботів з лабіринту та характерні числові характеристики, які дозволили визначити головні залежності їх поведінки.

***Ключові слова**: системи активної матерії, кластеризація, дослідження, спостереження, візуалізація результатів, арени, боти, застосунок для дослідження.*

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