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RAPID COMMUNICATION

Controlling the dynamic behavior of decentralized cluster through centralized approaches

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How to control the dynamic behavior of large-scale artificial active matter is a critical concern in experimental research on soft matter, particularly regarding the emergence of collective behaviors and the formation of group patterns. Centralized systems excel in precise control over individual behavior within a group, ensuring high accuracy and controllability in task execution. Nevertheless, their sensitivity to group size may limit their adaptability to diverse tasks. In contrast, decentralized systems empower individuals with autonomous decision-making, enhancing adaptability and system robustness. Yet, this flexibility comes at the cost of reduced accuracy and efficiency in task execution. In this work, we present a unique method for regulating the centralized dynamic behavior of self-organizing clusters based on environmental interactions. Within this environment-coupled robot system, each robot possesses similar dynamic characteristics, and their internal programs are entirely identical. However, their behaviors can be guided by the centralized control of the environment, facilitating the accomplishment of diverse cluster tasks. This approach aims to balance the accuracy and flexibility of centralized control with the robustness and task adaptability of decentralized control. The proactive regulation of dynamic behavioral characteristics in active matter groups, demonstrated in this work through environmental interactions, holds the potential to introduce a novel technological approach and provide experimental references for studying the dynamic behavior control of large-scale artificial active matter systems.

Keywords: self-organizing system, centralized control, dynamics regulation

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1. Introduction

Precise control of artificial active matter groups is a pivotal aspect in experimental investigations of emergent dynamics within active matter.[1–3] Traditionally, chemical methods have been extensively utilized to induce microscopic movements and interactions among particles in granular systems,[4,5] leading to the emergence of macroscopic patterns or phase transition phenomena.[6,7] Additionally, specialized artificial active materials like Janus particles[8] and magnetic particles[9] can be manipulated using various stimuli such as light,[10] magnetic forces,[9,11] and electric fields.[12] When subjected to external forces or input energy, these systems demonstrate a wide array of collective behaviors.[1] Moreover, a burgeoning area of interest involves the exploration of collective dynamics in active matter through the assembly of robot clusters.[13] Unlike microscopic particles, robot individuals possess programmable and quantifiable characteristics, offering distinct advantages in the investigation of active matter systems.[14,15]

In diverse active matter systems, a categorization based on control methods reveals a distinction, particularly in the case of centralized control systems. Within such systems, individual behaviors are regulated by a central entity or device node.[16] The central node or controller must possess comprehensive information about the behavior characteristics and positions of all individuals,[17] enabling global coordination, decision-making, and task distribution.[18] For various tasks, the central entity must formulate distinct control strategies tailored to the task requirements and communicate them to individuals assigned specific roles. Individuals are also required to reprogram or adjust their dynamic characteristics and update their mechanical structures based on task specifications.[19] These systems exhibit high efficiency in task completion, as tasks can be meticulously planned,[20] providing each individual with a clearly defined action path and precise motion instructions. However, the computational complexity and control intricacy escalate rapidly with an increase in cluster size due to the central node managing information about all individuals and the environment, as well as devising strategies

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for each individual based on task requirements. Consequently, this results in a precipitous decline in system control efficiency and an increased susceptibility to errors.[21]

As a solution to these challenges, eliminating centralized control and adopting a localized decision-making approach emerges as an optimized choice for multi-individual cluster tasks. This decentralized self-organizing system is characterized by individuals with similar functions, lacking an independent control center within the system.[22,23] Individual programs are pre-established, allowing each individual to make autonomous behavioral decisions based on real-time environmental conditions and interactions with others.[24] These systems display relatively flexible task adaptability and environmental responsiveness.[25] The inherent self-similarity among individuals contributes to strong functional robustness within the cluster. A noteworthy feature of self-organizing groups is their ability to dynamically scale, rendering the group's functionality insensitive to the quantity of individuals.[26]

The phenomenon of self-organization is prominently observed in various active matter systems, encompassing biological communities[27] such as flocks of birds, schools of fish, and cell colonies, as well as artificial systems like Kilobot,[28] particle robotics,[29] and vibration-driven robots.[30] Despite the clear advantages of self-organizing cluster systems, their decentralized decision-making nature poses challenges in ensuring global optimality during task execution. Consequently, compared to centralized planning, decentralized systems often lag behind in terms of task efficiency and accuracy.

Harmonizing the benefits of both centralized and decentralized systems to ensure task completion efficiency and accuracy, along with maintaining adaptability, scalability, and flexibility in cluster dynamics, constitutes a crucial challenge in the study of dynamic behavior regulation. Prior research has explored various approaches, including the utilization of multiple central nodes to replace a single node, thereby mitigating the complexity of cluster task planning.[31] Some studies have ingeniously designed group tasks, allowing individual task adaptability through straightforward macro control, achieving efficient group task completion without escalating central control complexity.[16,32] The exploration of information sharing among individuals has also been undertaken to facilitate independent decision-making with global information reference, circumventing local optimal solutions and approximating characteristics akin to centralized control in decentralized groups.[33] However, these methods often necessitate individuals with complex functionalities and robust computational capabilities, posing challenges when dealing with simpler individuals unable to share information.

In this study, we introduce a centralized dynamic behavior regulation method and system for self-organizing clusters based on environmental influence. Within this system, a decentralized self-organizing group of robots has its dynamic behavior and tasks regulated through centralized control. Each robot possesses the ability to perceive the color environment generated by an LED screen capable of displaying various colors, with a central computer controlling the dynamic changes in the environment. All robots within the system have nearly identical structures, functionalities, and programs. Controlling the local environment of individuals in the group through the optical environment platform enables indirect control of the dynamic behavior of individuals.

Through a series of experiments, we demonstrated that individuals adhered to a consistent phototactic rule in all scenarios. Despite their simplicity and inability to share information, they accurately and efficiently completed a variety of group tasks, including formation, transfer, item transportation, and structural shaping. The group displayed adaptability to varying quantities, robustness to initial conditions, and interference resilience during operations, achieving the goal of preserving the advantages of a decentralized system while incorporating the efficiency and accuracy of centralized control. The proposed environment-coupled cluster robot system and the concept of environmental-based centralized control offer a new perspective and solution for finely regulating the dynamic behavior of active matter clusters. This addresses the inherent contradiction between centralized control and decentralized features in multi-agent systems.

2. Methods

2.1. Robots and environmental platform

The environment in the real world is often characterized by complexity and variability, featuring elements that are challenging to control and quantify. Constructing a simulated environment for a robotic collective within a laboratory setting is an optimized choice. Figure 1(a) illustrates the robot used in this study. Each robot has two symmetrically mounted wheels that can operate independently, ensuring the ability to move in any direction. Four color sensors distributed at the bottom of the robot can independently detect the light intensity information at four positions, allowing the robot to perceive the direction of light intensity gradients in the local environment. The red LED on the top of the robot is used to indicate the real-time position to the camera system.

Robots move on the LED screen placed on the ground, serving as the environment, as shown in Fig. 1(b). The distance between the LEDs on the screen is 1.25 mm, and each LED can emit colored light of varying intensities independently. As the robot moves on the LED platform, it makes motion decisions based on the light intensity distribution detected by the four color sensors at the bottom. The camera system above the platform identifies the real-time position of

each robot through the recognition of the red LED light on the robot's top. This positional data is then transmitted in real time to the control computer on the side.

The computer calculates the next movement direction of the robot group based on the specific task and updates the new gradient information on each robot's bottom. Individuals change their movement direction upon detecting changes in light intensity gradients. Thus, a closed-loop centralized control system is formed, with the computer as the task calculation center. It plans tasks based on the positions of all robots obtained from the camera and indirectly controls the movement of each robot by displaying different light intensity gradients on the platform. It is crucial to emphasize that, in this system, the central computer does not issue direct commands to the robots. Instead, each robot's movement decision is made spontaneously based on the detected light intensity gradient information. In other words, the central computer can only determine the environmental information, indirectly influencing the movement behavior of individual robots, and cannot directly dictate the specific movements of the robots. The computer and the robots are two independent decision systems without direct communication, achieving indirect interaction through the environment. This approach ensures that the robot group can maintain decentralized characteristics.

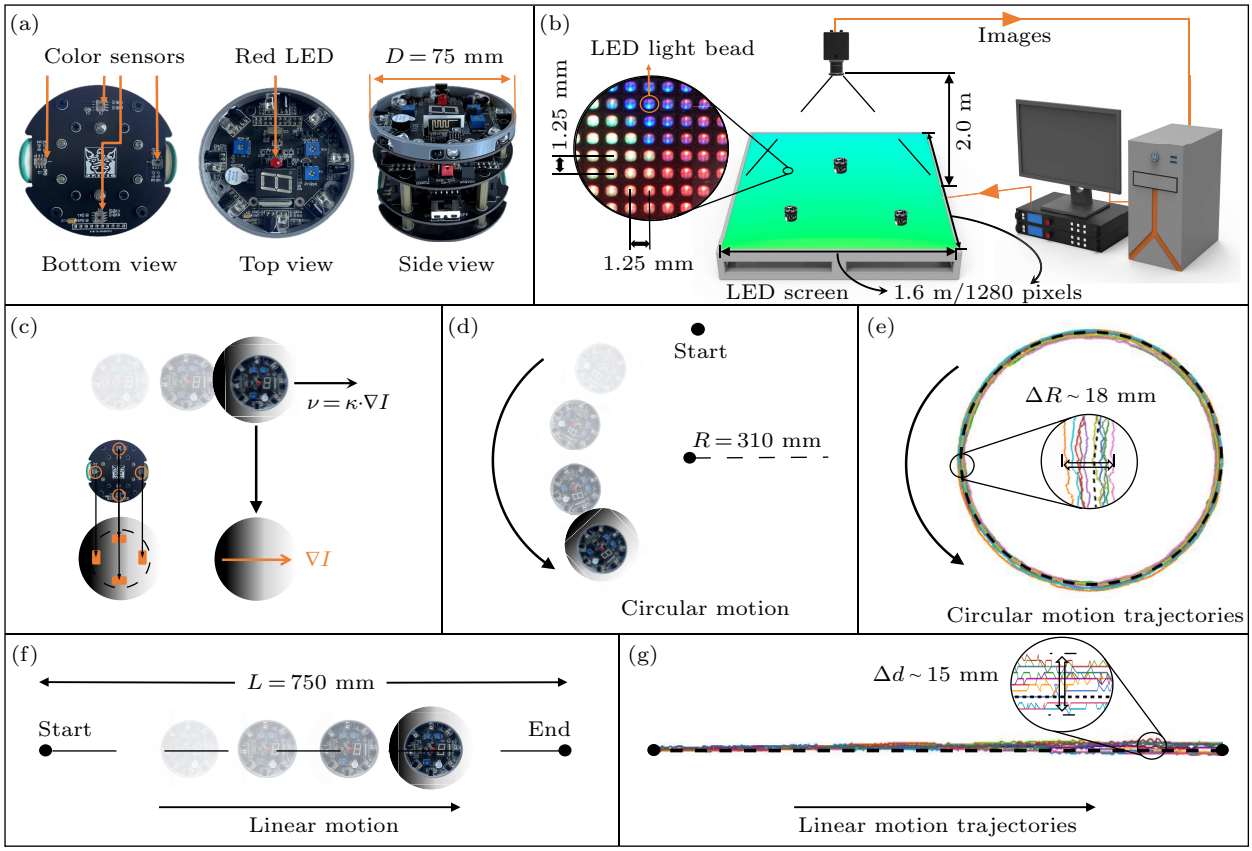


Fig. 1. Robot and experimental platform. (a) Structural overview of the robot in different directions. In this work, only partial functionalities of the robot were utilized. (b) Virtual environment platform constructed by an LED screen, where the robotic collective moves on the LED screen, and the top camera can track individual positions in real time. The screen is dynamically controlled by a computer to facilitate real-time changes in the environment. (c) Phototactic motion of the robot driven by light spots with gradient directions. (d) Circular motion of the robot driven by the light spots. (e) Trajectory plots from 10 consecutive circular motions, revealing a maximum radial error of 18 mm. (f) Linear motion of the robot driven by the light spots. (g) Trajectory plots from 10 linear motions, indicating a maximum deviation of 15 mm in straight-line motion.

2.2. Methods for driving robot motion

To embody the basic characteristics of self-propelled active matter and the adaptability of decentralized groups to diverse tasks, in all experiments described below, robots are embedded with an identical motion-driving rule: move along the direction of the light intensity gradient. The establishment of this rule is inspired by foraging behaviors observed in the natural world among organisms such as cattle, sheep, bacteria, and cells. In this system, color brightness is regarded as resource intensity, thus individuals are programmed to move towards areas with higher resource availability. In other words, the decision for each robot's movement is based on detecting the light intensity distribution in its environment and moving towards the direction of higher light intensity. Figure 1(c) illustrates a schematic diagram of guiding an individual robot's movement with a gradient-oriented light spot. When the light intensities detected by the four color sensors are denoted as I_1, I_2, I_3, and I_4, the individual's movement speed v is given by

the equation

$$v_n = \kappa \cdot \nabla I(x_n, y_n) = \kappa \cdot [(I_1 - I_3) - (I_2 - I_4)] \cdot d^{-1}, \quad (1)$$

where κ represents the individual's sensitivity to the light intensity gradient, and d is the distance between the color sensors. Adjusting κ allows changing the robot's dynamic response to the gradient. Upon perceiving the light intensity gradient, the individual robot executes a single movement step. However, due to inherent sensor noise in real-world robotic systems and the relatively coarse-grained nature of detection by the four color sensors in capturing local gradients, the direction of an individual's single-step movement may not align perfectly with the light intensity gradient direction. Nevertheless, after each movement step, the robot undergoes a reevaluation of environmental information and proceeds to execute the next movement step. Consequently, despite the initial inconsistencies, the collective trajectory of the robot individuals ultimately converges towards the expected set goals.

As depicted in Fig. 1(d), guiding individual robots to execute basic circular motion involves specifying the position of the light spot and the gradient direction corresponding to the desired circular motion and rotation angle. The trajectory and deviation after an individual completing continuous rotation for 10 cycles of circular motion are illustrated in Fig. 1(e). The actual trajectory exhibits multiple straight-line segments, with an inner and outer radius deviation of approximately 18.0 mm. As shown in Fig. 1(f), when guiding individuals to perform linear motion, it is only necessary to maintain the gradient direction of the light spot and translate the light spot at a constant speed to drive the individual to generate linear displacement. Figure 1(g) illustrates the actual trajectory of an individual performing independent linear driving motion for 10 consecutive times. Due to noise and deviation in motion, the robot's trajectory may oscillate near the ideal straight-line trajectory, with a maximum deviation of 15 mm. It should be noted that if the speed of light spot movement exceeds the robot's fastest movement speed, the robot may not keep up with the light spot, leading to the failure of overall motion. Similarly, for more complex motion trajectories, changing the light spot's position and rotation direction can drive the robot to exhibit the expected behavioral patterns. When multiple individuals are present in the environment, different movement patterns for the group can be achieved by assigning different light spot positions and directions to each individual.

It is essential to highlight that, compared to fully centralized control, in this system, individuals can autonomously handle real-time light gradient information, overcoming system noise and motion errors to achieve the central node's desired movement direction. For instance, when the light spot is stationary, or its motion speed is significantly slower than the robot's speed, individuals will repeatedly move within the same light spot. This is advantageous for individuals to correct occasional erroneous movement behaviors. A distinctive feature of the system lies in its macro-level implementation of centralized control while preserving decentralized characteristics at the individual behavioral level. Within this framework, each individual adheres to its internally embedded rule regarding the direction of light intensity gradients. Notably, their internal programs do not require differentiation among various tasks; hence, individuals remain oblivious to macro-level tasks. This explains the system's adaptability, wherein the same program can seamlessly accommodate a diverse range of tasks.

2.3. Experiment settings

The experiments were conducted within a display area of 1.6 m × 1.6 m on the LED screen. All robots were equipped with the same program. The set step length for each robot's movement was 2 cm. To minimize performance heterogeneity among robots, all individuals had the same initial battery level. The response time for individual localization detection and environmental updates was approximately 0.2 s.

To verify the system's ability to handle various task types, the experiments were divided into four different groups. The first group focused on static array configurations, evaluating the ability, efficiency, and accuracy of the group in forming specific structures through stationary movements. This included using 15 robots to construct triangular and circular array structures, as well as using 16 robots to form a square array. In all three experiments, the initial positions of individuals were randomly arranged, and the initial positions varied across three repetitions of the experiment. The target positions were fixed according to different shapes. Based on the real-time positions of individuals and their relationship to the target positions, the light spot drove the robots to move towards the nearest target point. In cases of target point competition, a simple principle of proximity rule was applied:

$$(x_{\text{aim}}, y_{\text{aim}}) = \min\left\{\sqrt{(x_n - x_i)^2 + (y_n - y_i)^2}\right\},$$
$$i = 1, 2, 3, \ldots, m. \quad (2)$$

The second group consisted of dynamic migration experiments for the cluster, including three different experiments. The first involved the collective rotation migration of a triangular array, arranging 15 robots into a triangular array and inducing the group to rotate collectively along one angle of the triangle under the influence of the light spot. The second experiment featured linear migration in different directions for a square array, arranging 16 robots into a square array and driving the group to undergo linear migration under the influence of the light spot. The third experiment involved 16 randomly distributed robots that, under the influence of the light spot, gradually converged or diverged in spiral-shaped motion,

eventually gathering within a fixed rotating orbit. The gradient direction α_n of the light spot corresponding to the position (x_n, y_n) of each individual was calculated by

$$\alpha_n = \tan^{-1}\left(-\frac{x_n}{y_n}\right) + \frac{1-\sqrt{x_n^2+y_n^2}}{\sqrt{1+(x_n^2+y_n^2)}} \cdot \frac{\pi}{2}. \tag{3}$$

In the third group of experiments, 16 robots were autonomously and continuously arranged from an initially randomly placed condition to form and deform into each letter of the word "ROBOTS". In the fourth group of experiments, a box with a weight of 80 g was placed in the middle of 8 robots. The robot group collaborated to push the box along a predetermined path, exemplifying collective efforts in object transportation.

3. Results and discussion

3.1. Individual dynamics behavior

The premise of controlling group behavior through environmental manipulation lies in the precise regulation of individual dynamic behavior. Figure 1(f) illustrates the results of 10 experiments involving the movement of robotic individuals under spot-induced linear motion. When the speed of individual robots matches the speed of spot movement, the overall trajectory of robot motion exhibits minimal deviation from the predetermined path. However, upon closer inspection of the motion details as Fig. 1(g) shows, it becomes evident that the actual robot movement is not a perfectly straight line. Instead, the robots oscillate left and right along the standard direction within the spot region. This aligns with the intuition for real systems, as inherent noise in the display of light color and sensor detection, along with the arrangement of the four color sensors, results in imperfect detection of actual light intensity gradients. Consequently, deviations from the standard direction are common during actual movements. Nevertheless, as the robots operate continuously, each movement cycle involves redetecting light intensity information before initiating the next move. This allows the robots to correct directional deviations over multiple movements, explaining the segmented nature of the robot's trajectory. In comparison to linear motion, circular motion demands more turning actions from individual robots. This requires high sensitivity to light intensity gradients and accurate motion and turning capabilities. Figure 1(e) presents the results of 10 experiments where individual robots executed circular motion induced by a predetermined spot, showcasing the remarkable characteristics of the robots in completing circular motion. The supplementary video 1 presents the dynamics of individual linear and circular motion.

It should be noted that if a robot's position exceeds the area of the spot, it may lead to the robot's front color sensor detecting a black region, causing the robot to perceive the direction with higher light intensity as behind it. This may occasionally result in a backward movement. Repetition of experiments with multiple robots also demonstrates the controllable heterogeneity of the robot group used in the experiments. Continuous linear and circular motion experiments suggest that, driven by the environmental spot, the robot group can reasonably achieve both linear and circular motion, indicating the feasibility of using the environment to design and drive individual behaviors.

3.2. Formation and transition of robot cluster

The establishment of stable and intriguing patterns in decentralized artificial active matter groups under specific conditions is pivotal for the exploration of emergent behaviors within clustered systems. Since each robot in a decentralized group is similar and ignorant of macro-level task details, achieving clustering generally requires setting interaction rules among individuals, utilizing effects such as repulsion and attraction to achieve macroscopic clustering phenomena. In our system, individuals similarly lack awareness of macroscopic tasks and focus exclusively on executing their phototactic movements. Macroscopic tasks are decomposed into individual actions through environmental light spots.

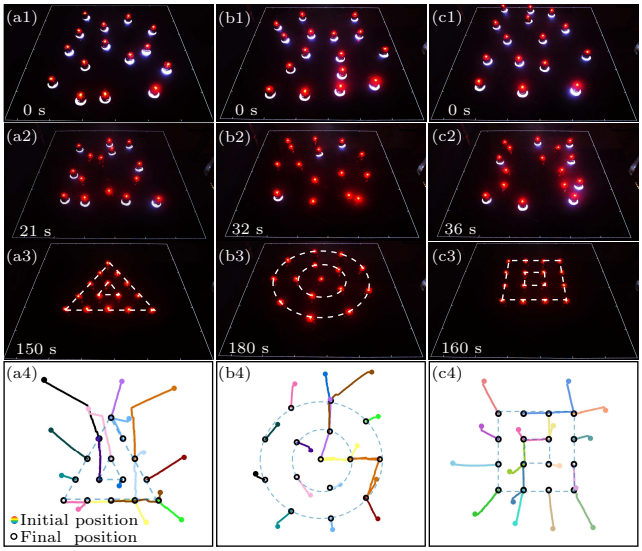


Fig. 2. Formation experiments of different cluster arrays. (a1)–(a3) The robotic collective transitions from an initial state of random distribution to the formation of a triangular array guided by centralized light spots. (a4) The actual trajectory plot illustrates the movement of robots from their initial positions to the target positions. The line segments in the trajectory represent the reselection of target positions for the robots. (b1)–(b3) The robotic collective gradually constructs a circular outline of the cluster array from an initially random distribution. (b4) The trajectory plot depicting the formation of a circular array. (c1)–(c3) The process by which the robotic collective builds a square array. (c4) Individual movement trajectory plots during the formation of the square array.

Figures 2(a3)–2(c3) respectively demonstrate experimental results of robot groups forming triangular, circular, and square arrays from an initially random distribution state induced by environmental light spots. During the process of

forming each array, each robot is undistinguished, meaning that in each experiment, robots at a specific target location are likely to be different. The formation of cluster patterns is insensitive to the initial state of the group; the environmental driving program can adaptively adjust the positions and directions of the robots, efficiently moving individuals to the target area based on a proximity principle. During the formation of cluster patterns, simultaneous actions among individuals may lead to congestion and collisions. Therefore, in practical implementation, the movement of robot swarms is dynamically divided into multiple phases based on the initial positions. Specifically, since individual movements are controlled by a central computer, the system adopts a proximity-based principle to plan the movement paths of each individual. If the trajectories of two individuals would intersect, one individual will pause and wait for the other to move away before continuing its motion. Consequently, from the experimental results, the movement of the swarm naturally divides into multiple stages, with the next stage of the swarm starting to move only after individuals in the previous stage have reached their positions. Thus, although the efficiency of swarm movement decreases, competition between robots' paths is avoided, ensuring the accuracy of task completion. Figures 2(a4)–2(c4) respectively illustrate the trajectories of individuals moving from the initial positions to target points when forming three different cluster arrays. The efficiency of the proximity principle in achieving targets is evident from the trajectory diagrams. Inflection points in the trajectories represent the dynamic establishment of new targets after an individual's target position is occupied. Supplementary video 1 illustrates the formation processes of three different arrays.

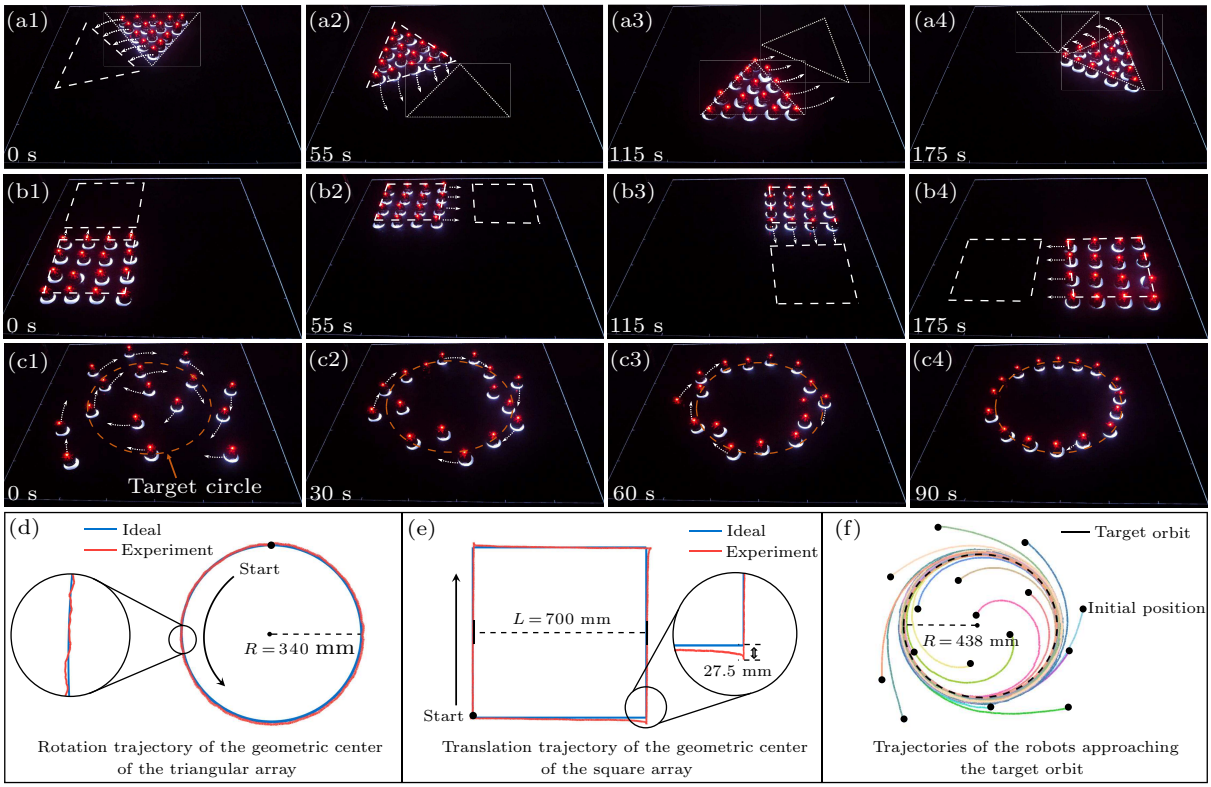


Fig. 3. Dynamic experiments of the cluster. (a1)–(a4) The group in a triangular array collectively rotates around one vertex of the triangle, maintaining the structure of the cluster array unchanged during the process. (b1)–(b4) All individuals in a square array synchronously undergo linear migration, demonstrating the capability for parallel migration in different directions. (c1)–(c4) The group gradually converges from an initially scattered state to moving along the same circular orbit through curved movements. (d) Comparison between the geometric center trajectory and the ideal trajectory during the collective rotation of the triangular array. (e) Comparison between the geometric center trajectory and the ideal migration trajectory during the continuous linear migration of the square array. (f) Individual trajectories illustrating the gradual convergence of the robot group from an initially scattered state to moving along the same target orbit.

Static cluster array experiments have successfully showcased the accuracy and efficiency of environment-driven self-organizing groups in configuring cluster formations. However, the migration of active matter groups presents an additional challenge. As depicted in Figs. 3(a1)–3(a4), experimental results illustrate a robot group rotating collectively around one vertex of a triangular array. In Fig. 3(d), the alignment of the ideal trajectory and the actual trajectory of the group center during the rotation process closely match, affirming the success of the rotational movement. Figures 3(b1)–3(b4) portray an experiment where the robot group undergoes parallel migration while steadfastly maintaining the cluster pattern. Figure 3(e) further demonstrates that, during migration, the ideal trajectory and actual trajectory exhibit only a 27.5 mm discrep-

ancy at turning points, attesting to the system's high accuracy in movement. In the realm of active matter, groups often form dynamic colonies with specific geometric structures, capable of flexible migration in the environment — examples include flying flocks of birds, swimming schools of fish, or mobile ant colonies. Such dynamic cluster migration necessitates the maintenance of relative positions among individuals while migrating in a predetermined direction. The experimental results of the robot group effectively showcase the characteristics of typical cluster rotation and migration. Despite their individual lack of awareness of the overall situation, these robots adeptly execute meaningful cluster behaviors on a macroscopic scale during their individual movements.

When the cluster's objective is not a specific target position or direction but rather a target area, the group demonstrates a dynamic adaptive process toward the goal. As depicted in Figs. 3(c1)–3(c4), the scenario unfolds as the group transitions from a random dispersion to moving along a predefined circular orbit. The angle of each individual toward the orbit increases proportionally with its distance from the target orbit, eventually resulting in all individuals converging in a curved motion onto the same circular orbit, maintaining dynamic movement. Figure 3(f) shows the trajectories of each robot moving to the target orbit. In this experimental process, the environmental program adapts to the robot's position and quantity. The number of robots can dynamically increase or decrease, and the robot's position can be disturbed or disrupted. Nevertheless, the group can reassemble on the orbit, showcasing robustness in face of challenges. This scalability and robustness arise from the decentralized nature of the group. Supplementary video 2 showcases the processes of group rotation, migration, and dynamic aggregation.

3.3. Complex group tasks

In the aforementioned experiments, both the robot group and the environmental system successfully executed individual tasks. To verify the system's ability to adapt to continuous tasks, figures 4(a1)–4(a12) show the robot group achieving a continuous transformation of the cluster configuration to form the word "ROBOTS" from the first letter "R" to the last letter "S". In this experiment, the initial positions of the robots were randomly placed, and the robots were dynamically planned to the corresponding positions of the letters. After completing one letter, it served as the initial state to construct the next letter. During the letter transformation process, if consecutive pairs of letters occupy the same position, individuals positioned at those specific locations do not need to move further. The vacant positions will be filled by neighboring robots. Determining which individuals need to move and which ones can remain stationary is centrally computed by the central computer. The total duration for completing all letters continuously is approximately ~ 15 minutes. The implementation of continuous tasks imposes high requirements on the stability and accuracy of each individual in the cluster, demonstrating the cluster's continuous adaptability to diverse tasks.

Collaboration is a crucial topic in tasks involving intelligent agents in active matter clusters, such as ants cooperating to transport large food that cannot be handled by a single ant. Many artificial active matters can also cleverly achieve significant group functions by aggregating a large number of individuals. Figures 4(b1)–4(b3) illustrate the experimental results of a robot group cooperating to transport a target object (a cardboard box) along a specific route. The individuals in the cluster not only apply force to the target object but also play a crucial role in maintaining the position of the target object within the cluster. This experiment verifies that the system can exert an influence on the target object based on the cluster, in addition to position-based tasks. Supplementary video 3 presents the experiments where a robot group accomplishes continuous deformation tasks and collaboratively transfers the target object.

It is worth noting that in all the different tasks described above, the actual running paths of the robots are not pre-set but dynamically planned based on the actual situation during task implementation. Therefore, even if a robot experiences a decrease in operational efficiency or accuracy due to malfunctions or unstable performance, it does not affect the overall task implementation, with the trade-off being an extended time requirement. Thus, from a technical perspective, the system's resistance to interference during the experiment is extremely strong.

Compared to a central computer issuing very specific motion path planning to each individual, and even detailing each behavior, this system's central control node only needs to compute the overall movement trajectory, without concerning itself with the specific movement details of each individual. This results in lower efficiency compared to artificial potential field path planning systems, but it maintains advantages in terms of computational burden and complexity at the central node. Additionally, since individuals in this system cannot directly communicate with the host, they cannot obtain real-time information regarding the calculated individual movement speed and direction based on artificial potential field theory. This is a limitation of the system, but it also suggests that when a group cannot directly communicate with the host, programmable environments can be considered to achieve similar effects. By accurately calculating the gradient of each individual's spot using artificial potential field theory and avoiding positional competition among them, it may be possible to further enhance the system's efficiency.

From a theoretical standpoint, as macroscopic tasks transition from simple to complex, the complexity increase is pri-

marily reflected in the increased computational demands on the central computer serving as the control node. Consequently, the system's complexity can be significantly reduced. This highlights the advantage of using centralized control to drive decentralized groups through the environment to complete macroscopic tasks in a localized manner.

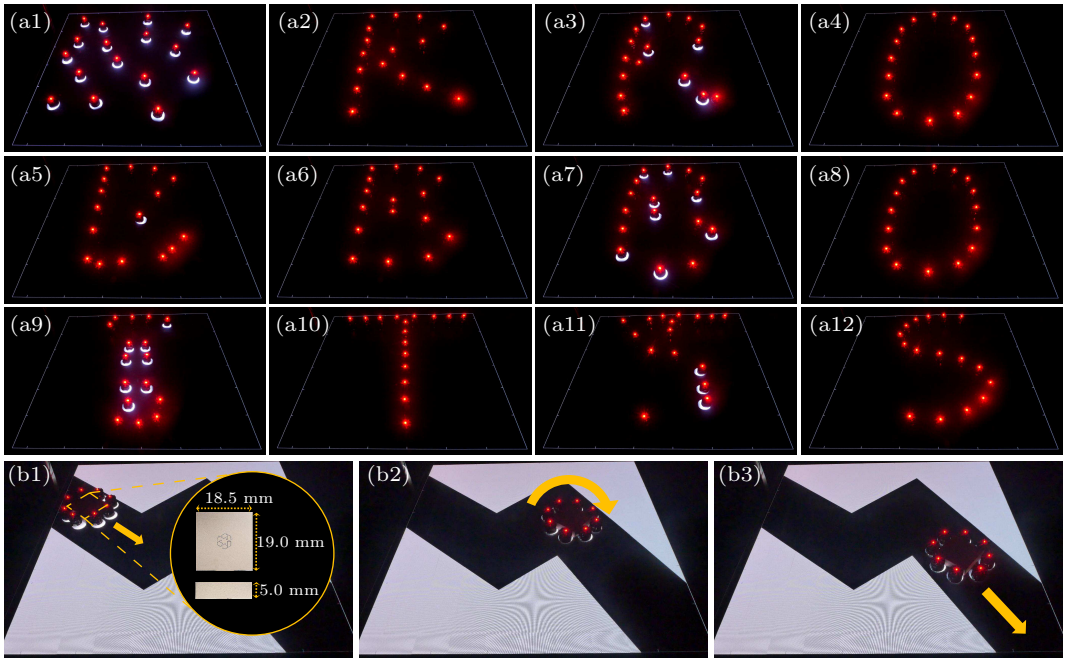


Fig. 4. Experiments of robots completing complex tasks. (a1)–(a12) The robot group continuously completes the shaping and deformation of the six letters in "ROBOTS" from an initially scattered state. The starting point of the deformation for each letter is the endpoint of the preceding one. (b1)–(b3) Eight robots collaborate in transporting a target cardboard box through a narrow passage. Throughout the transportation process, the relative positions of individuals within the group remain unchanged.

4. Conclusion

In the realm of artificial active matter systems, achieving flexible control is a critical imperative for experimental research. However, common systems, whether centralized or decentralized, exhibit inherent limitations, including issues with individual adaptability, sensitivity to quantity, and efficiency–accuracy trade-offs. In response, we propose and validate a novel approach to centrally control the dynamic behaviors of self-organizing clusters through environmental interactions within an environment-coupled swarm robotics system. In this system, we demonstrate that individual robots, equipped with a simple phototactic rule, can collectively address macroscopic tasks guided by a central computer. This central node dynamically plans ideal paths based on task requirements and real-time cluster positions, inducing individuals to move through the display of light spots with intensity gradients on the environmental platform. Remarkably, individual robots autonomously handle system noise, anomalies, and heterogeneity, successfully accomplishing macroscopic tasks of varying complexities.

We quantify the feasibility and accuracy of this concept by driving individuals to perform linear and circular motions. Then, we arrange randomly placed clusters into typical triangular, circular, and square arrays, validating the ability of the system to form static patterns. Furthermore, through experiments, we confirm that the system can not only manipulate the formation of specific arrays but also drive the entire cluster to rotate or migrate collectively. Additionally, experiments with dynamic circular target trajectories demonstrate the dynamic attributes of the cluster when adapting to broad objectives. To explore the system's capability to accomplish more complex tasks, we validate its dynamic adaptability by having the cluster continuously transform into multiple letters in a single task. Moreover, by mimicking ants carrying food, we demonstrate that this cluster system can also accomplish the task of transporting a target along a predefined route, showcasing the cluster's ability to interact with external systems.

This series of static, dynamic, and complex tasks thoroughly illustrate the characteristics of centralized control based on environmental influences for self-organizing clusters. It is noteworthy that in all the described experiments, the internal code and rules of the robots remained unchanged, emphasizing the diverse functionality and robust performance inherent in self-organizing groups. Furthermore, in this system, the central control node can customize the drive for each individual according to macroscopic task requirements. However, compared to traditional multi-agent control systems, the central control node in this system does not need to compute every detail of each individual's actions; it only needs to provide an ideal task completion path. The details of task implementation can be actively adjusted and corrected by the adaptability of in-

dividual robots to the environment. Thus, the system ensures the accuracy and efficiency of centralized control, reducing the computational pressure on the central node.

This system and method can be employed for interventions requiring movement of particle swarms in active matter experiments. Apart from considering single-point control methods such as laser spot driving or bulk control methods like heating, a programmable environmental platform (utilizing light, electricity, heat, magnetism, etc.) can be designed. This allows particles with environmental field sensing capabilities to exhibit centralized control effects without altering their own attributes. This facilitates functionalities such as arranging, moving, forming, and deforming of particle swarms, presenting a more flexible approach to swarm control.

In conclusion, we demonstrate that self-organizing clusters, under the centralized control of a central node based on environmental interactions, can simultaneously encompass the performance robustness, functional diversity, and environmental adaptability of decentralized self-organizing systems, as well as the efficiency and accuracy characteristics of centralized control systems in implementing macroscopic tasks. This provides a new technical approach and experimental reference for the study of dynamic behavior control in active matters, especially for large-scale artificial active matter systems.

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