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Massive self-organized shape formation in grid environments

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Self-organized shape formation can be observed in many natural processes [1, 2], involving crystallization, multi-cellular organism formation, and social insects collaboration. In these natural processes, complex structures emerge from decentralized collaboration among individuals. This kind of phenomenon motivates two research problems: what is the mechanism of self-organized shape formation, and how to construct artificial systems of self-organized shape formation. Solutions to the two problems could facilitate the application of self-organized shape formation in many potential domains, such as smart warehouses [3] and intelligent transportation [4]. Specifically, self-organized shape formation can be applied to bike-sharing systems in the intelligent transportation domain to guide the movement directions of multiple uses when the parking space is scarce.

In recent years, many attempts have been made to address the two problems mentioned above. Rubenstein et al. [5] proposed a method to support shape formation with thousands of agents based on the strategy of edge-following, which manifests low efficiency due to the low parallelism among agents. Yu et al. [6] proposed a centralized method for shape formation based on task assignment and path planning, which suffers from poor scalability concerning the number of involved agents due to the high computational cost. Chiang et al. [7] proposed a shape formation method based on the concept of artificial potential fields (APF), which exhibits poor stability due to the high risk of an agent's falling in local minima. To our best knowledge, there still lacks an efficient, scalable, and stable mechanism of self-organized shape formation in existing research and practice.

In this article, we demonstrate an approach to massive self-organized shape formation in grid environments. The essence of this approach is a continuously executing loop of information exploration, integration, and feedback among agents in a collective, following a constructive model for collective intelligence [8]. In particular, an artificial light field (ALF) is introduced and superimposed on the grid environment, serving as a carrier for information integration and feedback. As a result, a mutual feedback process emerges between the ALF and the agent collective: the current positions of all agents in the grid environment determine the current state of the ALF, which in turn drives agents to change their current positions.

Figure 1 gives an overview of this approach, which consists of five components: a grid environment, a target shape, an agent collective, an artificial light field, and a lightweight coordinator. In the shape formation process, each agent interacts with the coordinator through an iterative process. At the beginning of each iteration, each agent in the collective sends its current position to the coordinator; after receiving all agents' positions, the coordinator broadcasts system state to all agents. Then, each agent sequentially carries out three actions (local ALF calculation, priority queue generation, and conflict resolution) to obtain its next position. After that, each agent moves to its next position, informs the coordinator of this movement, and enters the next iteration. This iterative process terminates when the target shape is formed.

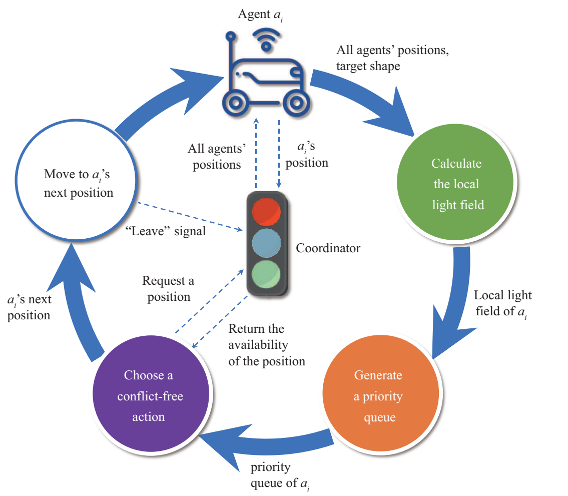

Figure 1 (Color online) An iterative process for ALF-based massive self-organized shape formation.

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We briefly describe the three kinds of agent action aforementioned as follows:

(1) Local ALF calculation. This step is responsible for calculating the local ALF of each agent, i.e., the light intensities in its surrounding 8 grids as well as its current position after receiving the current system state from the coordinator. Inspired by phototaxis observed in many species (i.e., organisms' movement towards or away from light sources) [9], we define two kinds of light: at any time, each agent out of the shape releases red light, and each unoccupied target grid releases blue light. The ALF at any time is defined as a pair of functions: the first function maps each grid to the intensity of red light at the grid, and the second to the intensity of blue light. The intensity of the light is attenuated with propagation distance. The intensity of red/blue light at a grid is the sum of all red/blue light's intensities propagated to the grid.

(2) Priority queue generation. Given an agent at an iteration, its priority queue of next positions is a permutation of this agent's local 9 grids, generated based on its local ALF. The strategy for generating an agent's priority queue depends on the agent's state. When an agent is outside the target shape, its priority queue will be constructed following the strategy of directing agents outside the target shape to move towards the shape. When an agent is already inside the target shape, its priority queue will be constructed following two strategies: the first strategy motivates an agent to keep moving towards those unoccupied positions in the center of the target shape after the agent has entered the shape, and the second one motivates an agent to leave peripheral positions of the target shape.

(3) Conflict resolution. After obtaining its priority queue, an agent will request the coordinator to check positions in the priority queue sequentially until finding a conflict-free next position. Specifically, each grid in the environment is treated as a mutex lock, and a try_lock mechanism is used to check whether a requested position is available. If the position is unavailable, the mechanism will check the next one in its priority queue immediately, avoiding the possible dead-lock in a wait_until_lock mechanism. This iterative negotiation will terminate until finding a conflict-free next position. In the extreme case when the priority queue becomes empty and the negotiation has not terminated, the agent will stay still at this time step.

Note that system states can also be shared among agents through broadcasting or cloud/edge nodes in the cloud-edge computing environment instead of the central coordinator, which can mitigate the coordinator's possible single-point failure problem.

In our experiments, this approach exhibits high efficiency, scalability, and stability. (1) In an extreme case involving 5469 agents in 135×135 grid environment, this approach forms the target shape accurately with only 119 steps/256.6 s on average. (2) Compared with the state-of-the-art centralized distance-optimal algorithm, this approach exhibits an n^3 to $n^2\log(n)$ decrease in the absolute completion time of the shape formation tasks with regard to task scale n, and can be easily accelerated via parallelization. (3) The standard deviations of the shape completion degree, the number of iterations to complete a target shape, and the physical time to complete a target shape of this approach are 0.00034, 0.04410, and 0.00033, respectively.

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Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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