Gene Regulatory Networks with Asymmetric Information for Swarm Robot Pattern Formation

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Abstract. Gene Regulatory Networks (GRNs) play a central role in understanding natural evolution and development of biological organisms from cells. In this paper, inspired by limited neighbors' information in the real environment, we propose a GRN-based algorithm with asymmetric information for swarm-robot pattern formation. Through this algorithm, the neighbors' information will be only used once, swarm robots can collect limited neighbors' information to self-organize autonomously to different predefine shapes. Furthermore, a discrete dynamic evolvement model of cellular automaton of pattern formation is provided to demonstrate the efficiency and convergence of the proposed method. Various cases have been conducted in the simulation, and the results illustrate the effectiveness of the method.

Keywords: Gene regulatory networks · Swarm robots · Pattern formation · Asymmetric information · Cellular automaton

1 Introduction

A very simple rule has been revealed again and again by the nature that extremely complicated phenomenons can emerge from simple agents with limited interactions. In order to reveal the mechanism of complexity emerging from interactions of simple agents, some concepts have been proposed inspired by the behaviors of ant colony, school of fish, flock, etc, just like Swarm Intelligence, Synergetics, Artificial Intelligence, Self-Organized Network, Evolutionary Learning, Complexity [1], [2], [3], [4]. The solution to this problem, in a sense, may be a candidate to explain the origin of life.

Pattern formation is a challenging part of this area. Various shapes can be self-organized generated with no central controller under natural conditions. In order to reveal the mechanism of pattern formation in the nature and to apply to swarm-robot pattern formation, many methods have been explored, such as: the L-systems and iterated function systems in fractal theory [5], cellular automaton modeling of biological pattern formation [6], using morphogen gradient [7], leader following algorithms [8], [9], potential field algorithms [10], [4], gene regulatory networks for swarm-robot pattern formation [11], [12], [13], [14], [15]. Challenges and classifications of pattern formation in existing literature are reviewed in [16].

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On the other hand, the existence of asymmetric information is a common phenomenon in the nature. Taking an example of visual, almost all animals have asymmetric eye positions, in other words, animals can not get neighbors' information all around, visual information is obtained asymmetrically or limitedly. Based on biological evolutionary theory, we can figure out that animals obtain asymmetric information on purpose and have asymmetric methods to deal with these asymmetric information. This strategy using asymmetric information means agent needs collecting less information and avoids information redundancy problem. From the point of view of whole population, strategy using asymmetric information have contributed to the development and evolution of the population.

Taking an example of robots, when a robot deals with its neighbors' information, if the information have been used by its neighbors, these information will not be used again by the robot, the robot uses the rest of neighbors' information to compute its next time position. In other words, the information between two neighbors is only used once.

In this paper, we use gene regulatory networks with asymmetric information to study the influence of asymmetric information on swam-robot pattern formation. A discrete dynamic evolvement model of cellular automaton of pattern formation is proposed to demonstrate the converge efficiency and numerical simulations confirm the effectiveness of the proposed model.

The rest of this paper is organized as follows. Section 2 presents a problem statement including the definitions of symmetric information and asymmetric information. Section 3 presents two cellular automaton models of pattern formation in swarm-robot system, consisting of a symmetric information model and an asymmetric information model. Section 4 introduces a gene regulatory network algorithm with asymmetric information for pattern formation. Section 5 presents numerical simulations containing pattern formation with symmetric information and asymmetric information in different initial condition. Conclusions and future work are given in Section 6.

2 Problem Statement

As our starting point, we propose the following definitions for the strategy using neighbors' information.

Definition 1. *Symmetric information is a kind of information that is public to all of its participators, each of the participators will use this information to make decisions.*

Definition 2. *Asymmetric information is a kind of information that is not public to all its participators, only part of the participators will use this information to make decisions.*

This paper considers the problem of how swarm robots self-organize to different predefine shapes driven by gene regulatory networks with asymmetric neighbors' information. It is assumed that global 2D position is available for the robots, and robots can only detect single directional neighbors. In other words, the robots have vision blindness.

3 Cellular Automaton Models of Pattern Formation in Interacting Cell System

Cellular automaton is a discrete dynamic system. It has no central controller and is rule-based evolvement model, usually used to simulate the natural phenomenons. It has become paradigms of self-organized complex systems in which collective behaviors arise from simple interaction rules.

The following two CA models give a strong confirmation that symmetric neighbors' information and asymmetric neighbors' information can both guide swarm robots to evenly target shapes.

The game of one-dimensional pattern formation is assumed . There are seven robots which are too close for each other in a line. They need using their neighbors' information to self-organize to a evenly line. Table. 1 presents initial position and final position of these seven robots.

Table 1. One-dimensional pattern formation game

Initial position	1 2 3 4 5 6 7
Final position	1 2 3 4 5 6 7

3.1 Cellular Automaton Model of Pattern Formation with Symmetric Neighbors' Information

Neighbors' position information in both sides is collected by each robot. That is to say the information between two neighbors is symmetric information and will be used duplicated twice. Evolution rules are as follows:

(1) The robot can detect neighbors in both sides.

(2) The robot just moves one grid or keeps still during one time step.

(3) If there are two neighbors in both sides, the robot will keep still. If there is one neighbor in one of the sides, the robot will move to the opposite side for one grid. If two robots occupy one grid, both two will leave away this grid at next time step.

Table. 2 presents the whole evolution process of seven robots with symmetric information from the initial position to the final position. It is easy to see that robot 2 and 3 occupy the same grid at time step 3, the same thing happens to robot 4 and 5. This situation should be avoided because of severe collision.

3.2 Cellular Automaton Model of Pattern Formation with Asymmetric Neighbors' Information

Neighbors' position information is detected single-directly for some environment reasons or hardware limitations. That means the information between two neighbors is asymmetric information and should be only used once. In the following

Table 2. CA model with Symmetric information

Initial position													
				1	2	3	4	5	6	7			
1			1		2	3	4	5	6		7		
2			1	2		3	4	5		6	7		
3		1			23		4		56			7	
4		1		2		3	4	5		6		7	
5		1		2	3		4		5	6		7	
6		1	2			3	4	5			6	7	
7	1			2	3		4		5	6			7
8	1		2			3	4	5			6		7
Final position	1		2		3		4		5		6		7

asymmetric model, each robot can only detect right side neighbors. Evolution rules are as follows:

(1) The robot can only detect right side neighbors.

(2) The robot just moves one grid or keeps still during one time step.

(3) If there is a right neighbor, the robot will move one left grid next time step. If there is no right neighbor, the robot will keep still next time step.

Table. 3 presents the whole evolution process of seven robots with asymmetric information from the initial position to the final position. we can draw the conclusion that asymmetric information can also guide swarm robots to a evenly target shape. This method needs fewer time steps and has no severe collision, that means asymmetric information has better converge efficiency.

Table 3. CA model with asymmetric information

Initial position													
							1	2	3	4	5	6	7
1						1	2	3	4	5	6		7
2					1	2	3	4	5		6		7
3				1	2	3	4		5		6		7
4			1	2	3		4		5		6		7
5		1	2		3		4		5		6		7
Final position	1		2		3		4		5		6		7

4 GRN Model with Asymmetric Information

The dynamics of the GRN for multi-robot construction can be described by the following equations[14]:

$$\frac{dg_{i,x}}{dt} = -a \cdot z_{i,x} + m \cdot p_{i,x} \tag{1}$$

$$\frac{dg_{i,y}}{dt} = -a \cdot z_{i,y} + m \cdot p_{i,y} \tag{2}$$

$$\frac{dp_{i,x}}{dt} = -c \cdot p_{i,x} + k \cdot f(z_{i,x}) + b \cdot D_{i,x} \tag{3}$$

$$\frac{dp_{i,y}}{dt} = -c \cdot p_{i,y} + k \cdot f(z_{i,y}) + b \cdot D_{i,y} \tag{4}$$

where $g_{i,x}$ and $g_{i,y}$ denote the x-axis position and y-axis position of robot i respectively. $p_{i,x}$ and $p_{i,y}$ denote the velocity-like property of robot i along the x-axis and y-axis respectively. $z_{i,x}$ and $z_{i,y}$ are the gradients which carry the information of target shape. $f(z_{i,x})$ and $f(z_{i,y})$ are sigmoid functions.

where $D_{i,x}$ and $D_{i,y}$ are the sum of neighbors' information, neighbors' distance information is collected to avoid collision in this paper. We have two strategies using neighbors' information as proposed in section 3. We have strategy using symmetric information :

$$D_{i,x} = \sum_{j=1}^{N_i} D_{i,x}^{j} \quad D_{i,y} = \sum_{j=1}^{N_i} D_{i,y}^{j} \tag{5}$$

and strategy using asymmetric information:

$$D_{i,x} = \sum_{j=1}^{i-1} D_{i,x}^{j} \quad D_{i,y} = \sum_{j=1}^{i-1} D_{i,y}^{j} \quad 1 \underline{\leq} j \underline{\leq} N_i \tag{6}$$

where N_i denotes the number of neighbors of robot i, and $D_{i,x}^{j}$ and $D_{i,y}^{j}$ are the distance function between robot i and robot j, which is defined as

$$D_{i,x}^{j} = \frac{(g_{i,x} - g_{j,x})}{\sqrt{(g_{i,x} - g_{j,x})^2 + (g_{i,y} - g_{j,y})^2}} \tag{7}$$

$$D_{i,y}^{j} = \frac{(g_{i,y} - g_{j,y})}{\sqrt{(g_{i,x} - g_{j,x})^2 + (g_{i,y} - g_{j,y})^2}} \tag{8}$$

Under the strategy using asymmetric information, robots are numbered clockwise and the robot on boundary $(-1, 0)$ is numbered 1 as show in Fig. 1. Robots can only detect low-number direction neighbors, so neighbors' information is only used once. For example, robot 6 can only select its neighbors from robot 1, 2, 3, 4 and 5.

Since the unit circle is a closed curve, the 1-st $(i = 1)$ robot is treated in a special way to satisfy the boundary condition. Specifically 1-st robot uses all its neighbors' information.

Mathematically, two distance function matrixes with symmetric information and asymmetric information present the differences between two strategies clearly. Symmetric matrix:

$$\begin{pmatrix} 0 & D_{12} & D_{13} & \cdots & D_{1n} \\ D_{21} & 0 & D_{23} & \cdots & D_{2n} \\ D_{31} & D_{32} & 0 & \cdots & D_{3n} \\ \vdots & \vdots & \vdots & 0 & \vdots \\ D_{n1} & D_{n2} & D_{n3} & \cdots & 0 \end{pmatrix} \quad D_{ij} = -D_{ji} \quad D_{ii} = 0 \tag{9}$$

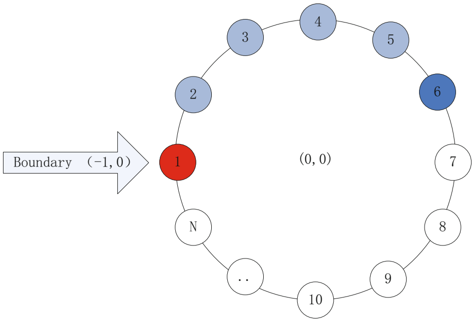


Fig. 1. The robots are numbered clockwise.

Asymmetric matrix or lower triangular matrix:

$$\begin{pmatrix} 0 & D_{12} & D_{13} & \cdots & D_{1n} \\ D_{21} & 0 & 0 & \cdots & 0 \\ D_{31} & D_{32} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 & \vdots \\ D_{n1} & D_{n2} & D_{n3} & \cdots & 0 \end{pmatrix} \quad D_{ij} = -D_{ji} \quad D_{ii} = 0 \tag{10}$$

The system's convergence to the target shape is proved according to the lyapunov theory [12]. The five parameters in the main system dynamics are optimized in [17].

5 Numerical Simulation

To evaluate the reliability and efficiency of the proposed methods, we perform a set of simulations using MATLAB.

In order to evaluate the evenness of the target shapes, we define the variance:

$$s^2 = \frac{\sum_{i=1}^{n} (d_i - d_0)^2}{n} \tag{11}$$

where d_i denotes distance between robot i and robot $i+1$ and d_0 denotes the expected distance value. The parameter s^2 should be as small as possible. In the following two cases, we assume that $s^2 = 0.001$ means that the uniform target shape is accomplished.

In order to ultimate uniform distribution of the robots, we define robots' neighbor range to be $d = \frac{L_{edge}}{N}$, where L_{edge} refers to the length of the target shape and N refers to the number of robots [18].

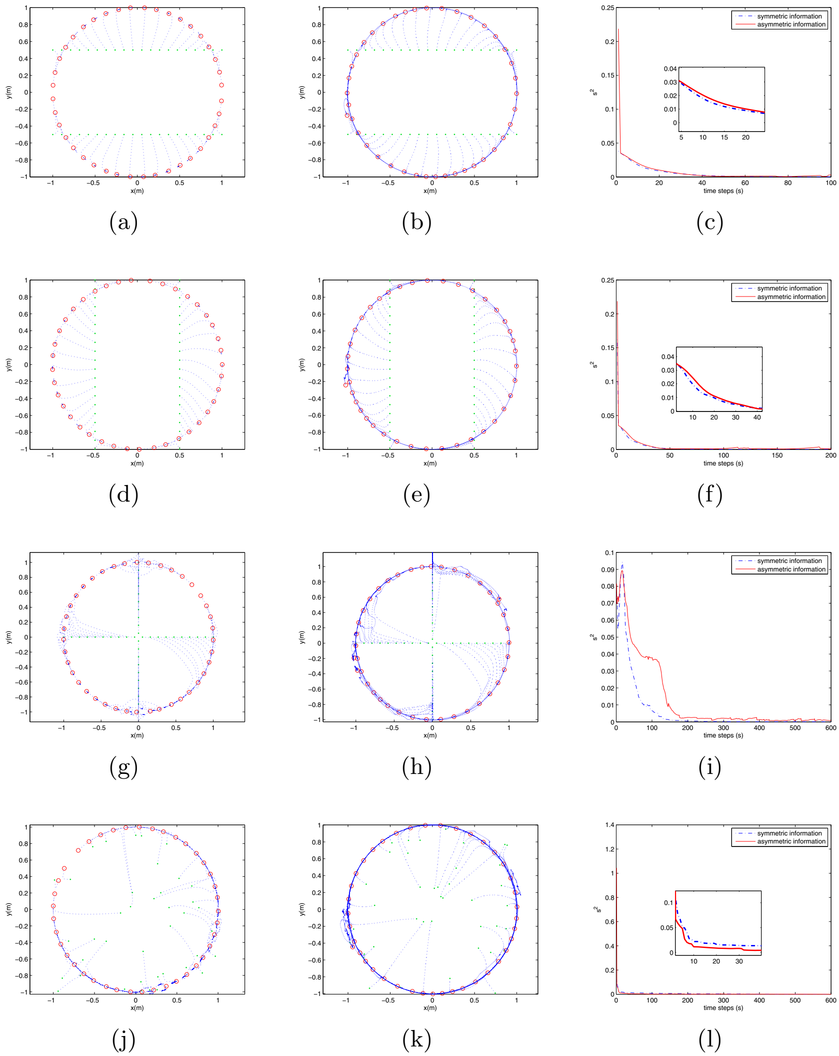


Fig. 2. The trajectories of 40 robots using GRN method to construct to a unit circle under different initial conditions. Initial position is denoted as a dot where final position is denoted as a small circle. (a) robots use symmetric information from two horizontal lines; (b) robots use asymmetric information from two horizontal lines; (c) s^2-time comparison curves from two horizontal lines; (d) robots use symmetric information from two upright lines; (e) robots use asymmetric information from two upright lines; (f) s^2-time comparison curves from two upright lines; (g) robots use symmetric information from two vertical lines; (h) robots use asymmetric information from two vertical lines; (i) s^2-time comparison curves from two vertical lines; (j) robots use symmetric information from a random square region; (k) robots use asymmetric information from a random square region; (l) s^2-time comparison curves from a random square region;

5.1 Case Study 1: Converge to a Unit Circle from Initial Symmetric Position

In this case, we deploy 40 robots to a unit circle from four different symmetric initial positions. Both strategies using neighbors' information are performed.

Fig. 2 shows that both strategies using symmetric and asymmetric information can guide the swarm robots to predefine target shapes. From the point of view of the converge time and efficiency, the four s^2-time comparison curves with different initial symmetric conditions show that there is no significant difference between two strategies under the same initial symmetric condition, but different initial conditions will lead to different converge time and efficiency no matter which strategy the robots uses.

5.2 Case Study 2: Converge to a Unit Circle from Initial Asymmetric Position

In this case, we deploy 40 robots to a unit circle from four different asymmetric initial positions. Both strategies using neighbors' information are performed.

Fig. 3 shows that if the robots are deployed to asymmetric shapes initially, the converge time is extended. Besides, we can figure it out that under the same initial asymmetric condition, the converge time of asymmetric strategy is largely shorter than that of symmetric strategy, that means the symmetric strategy needs less information but has better converge efficiency. Since the robots are always asymmetrically deployed in the real environment, the conclusion have a valuable meaning in application.

5.3 Results Analysis

Why the converge time of asymmetric strategy is largely shorter than that of symmetric strategy? In fact, robot collecting symmetric information moves very little or even don't move at each time step because of neutralization of distance information from its symmetric neighbors, while robot collecting asymmetric information doesn't face this problem, so it moves longer at each time step. Fig. 4(a) shows that under two horizontal lines initial symmetric position, total distance at each time step is not largely different, so the converge time is approximate. Fig. 4(b) shows that under one horizontal line asymmetric initial position, before 200 time step, total distance with asymmetric strategy is larger than that of symmetric strategy, so the converge time of asymmetric strategy is largely shorter than that of symmetric strategy.

5.4 Problem and Shortcoming

There are still many problems and shortcomings. As we can see from Fig. 2 and Fig. 3, the trajectories of second column of figures are more cluttered than that of first column. Fig. 3(e) and Fig. 3(k) show that there is a black regiment near the boundary position. In fact, when most robots have converged to the

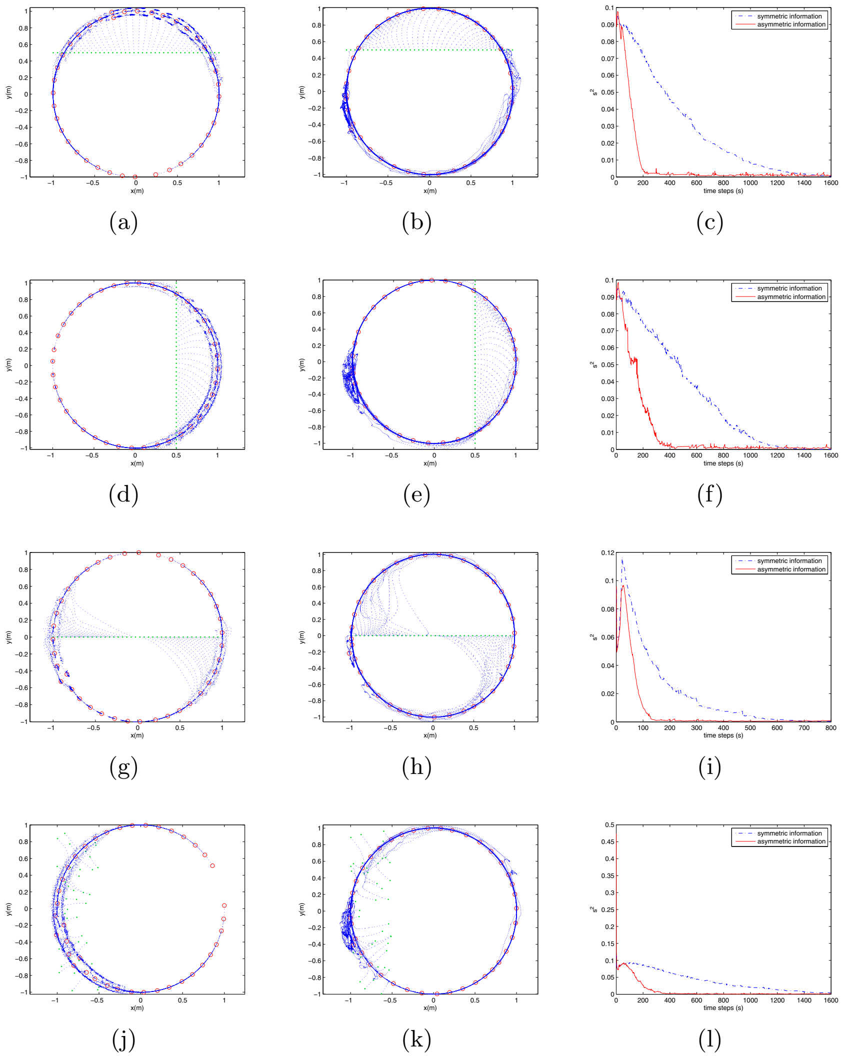
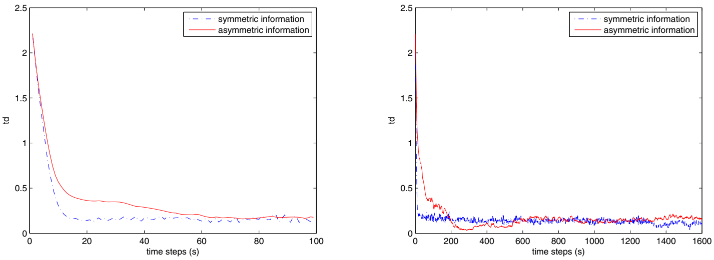


Fig. 3. The trajectories of 40 robots using GRN method to construct to a unit circle under different initial conditions. Initial position is denoted as a dot where final position is denoted as a small circle. (a) robots use symmetric information from one horizontal line; (b) robots use asymmetric information from one horizontal line; (c) s^2-time comparison curves from one horizontal line; (d) robots use symmetric information from one upright line; (e) robots use asymmetric information from one upright line; (f) s^2-time comparison curves from one upright line; (g) robots use symmetric information from x-axis line; (h) robots use asymmetric information from x-axis line; (i) s^2-time comparison curves from x-axis line; (j) robots use symmetric information from a random rectangle region; (k) robots use asymmetric information from a random rectangle region; (l) s^2-time comparison curves from a random rectangle region;



(a) two horizontal lines as initial position (b) one horizontal line as initial position

Fig. 4. Total distance at each time step

circle, there are still several unstable robots nearby the boundary position. These robots with their neighbors remain volatile for a long time that cause a black regiment and make trajectories more cluttered.

6 Conclusion and Future Work

In this paper, we have presented an asymmetric information-based gene regulatory network distributed control approach to multi-robot construction. Cellular automaton models of pattern formation and numerical simulation results show the effectiveness and advantages of the proposed method. The major conclusions are as follows:

(1) Both strategies using symmetric and asymmetric information can guide the robots to a predefine target shape, but the strategy using asymmetric information needs less neighbors' information.

(2) If the initial position is symmetric, there is no significant differences between two strategies, but if the initial position is asymmetric, the converge time of strategy using asymmetric information is largely shorter than that of symmetric information.

Numerical simulation results also show some problems, the trajectories under the strategy using asymmetric information are more cluttered and have longer total distance than that of symmetric information.

In the future, we will continue our research on asymmetric information and GRN-inspired multi-robot controllers. We will further investigate the proposed problems, especially boundary condition problem and use real robots to verify the effectiveness of the proposed method. We will also investigate the universality of asymmetric information in the natural world and compare the advantages and disadvantages of both strategies in detail.

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