

An Enhanced Multi-Agent System with Evolution Mechanism to Approximate *Physarum* Transport Networks

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Abstract. The primitive unicellular organism slime mould *Physarum Polycephalum* has attracted much attention from researchers of both biology and computer science fields. Biological experiments have revealed that its foraging mechanism can be used to solve shortest path problems, while its foraging process can construct efficient networks among food sources. Oregonator Model and Cellular Automaton have been proposed to simulate the intelligence and morphology of *Physarum*. To better understand the network formation of *Physarum*, a multi-agent system (MAS) model of particles was introduced by Jones, which can simulate many interesting patterns of *Physarum* transport networks. The MAS model is improved in three aspects: the number of sensors of each individual agent is reduced to two, while the function of each sensor is extended to sample both chemical nutrient and trail. A memory module is added to the architecture of an agent, by which the evolution mechanism can be achieved to maintain the population of the system. With such improvements, the system is more flexible and adaptive, and the networks constructed using the MAS model are more approximate to the ones by *Physarum* in biological experiments. All these are verified by constructing stable networks including Steiner's minimum tree, cycle-like and spanning trees.

Keywords: Multi-agent Systems, Population Evolution, *Physarum Polycephalum*, Transport Networks.

1 Introduction

Physarum Polycephalum, or the true slime mould, has been existing and evolving on the planet for millions of years. The multinucleated single-cell protist prefers darksome and moist environment. It feeds with fungal spores, bacteria and other microbes in nature and oat flakes in laboratories. The plasmodium is the most interesting phase in the life cycle of *Physarum*, in which it shows amazing behaviors such as establishing efficient transport networks with low cost and high

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fault tolerance [1,2]. Since Nakagaki found that *Physarum* can find the shortest path to solve maze problem [3], the intelligent behavior of *Physarum* has been the focus of researchers in various fields over the past decade.

Different methods have been proposed to analyze and simulate the intelligence of *Physarum*. Based on Hagen-Poiseuille equation in chemistry and Kirchhoff Law in physics, Nakagaki and Tero et al proposed a mathematical model to describe the feedback between flux and conductivity of the protoplasm tubes [4,5]. The model explains the adaptive feature of *Physarum* in maze-solving. It was also used to simulate the design of the railway network around Tokyo [6]. Inspired by the model, some modified methods are introduced to engineering technology, such as protocol design in Wireless Sensor Network (WSN) [7] and dynamic reconfiguration in service-oriented internet-ware systems [8]. Adamatzky conducted researches on *Physarum* in the perspective of reaction-diffusion. He treats it as a bio-realized unconventional computing substrate called *Physarum* Machine, and uses it to solve maze, graph problems and design logical gates [9]. Through the Oregonator model of Belousov-Zhabotinsky reaction, Adamatzky analyzes the common characteristics between *Physarum*'s foraging behavior and reaction-diffusion [10]. Gunji and Niizato et al, utilize Cellular Automata to simulate *Physarum* solving maze, Steiner minimum tree and spanning tree problems as well as *Physarum*'s motion and morphology [11], and reproduce adaptive and robust transport networks [12]. Jones presents a low-level particle-based agent model to approximate the network formation of *Physarum* [13]. In that model, a population of agents governed by the same rules resulted in their ordered arrangement, which is the emergence of networks in swarm. Other interesting features such as pattern formation of that model are discussed in [14] and [15].

The focus of this paper is mainly on the improvements of Jones' agent model to construct an enhanced multi-agent system. The improvements are in three aspects: 1) The environmental information sensed by the left and the right sensor is enough for an agent to choose its new direction, therefore we get rid of the forward sensor in Jones' model; 2) A Motion Counter is added to establish the evolution mechanism of the system, it actually works as a memory module; and 3) The trail and the chemo-nutrient, two chemo-attractants, are emitted by agents and food sources, respectively. Our sensor is able to distinguish the two chemo-attractants, and different weights are introduced to represent the corresponding influence of each chemo-attractant.

Based on the improvements, the pattern formation and flexibility of population on periodic and fixed boundary conditions are discussed. The enhanced MAS model is then employed to construct stable networks including Steiner's minimum tree, cycle-like and spanning trees. The results are compared with those constructed by *Physarum*. It shows that enhanced MAS can generate better networks – the networks are much closer to the ones constructed by *Physarum*.

In Section 2, the enhanced MAS model is discussed in details. Section 3 presents the approximation of *Physarum* transport networks using the improved MAS model. And finally, Section 4 is concluding remarks.

2 The Enhanced Multi-Agent System Model

This section discusses the improved MAS model in details. The architecture and behavior of individual agent are presented first, followed by other features of the model.

2.1 The Architecture and Behavior of a Single Agent

Our multi-agent system performs on the 2D scenario, which is divided into 200×200 square grids. A grid is a spatial unit, and the chemo-attractants diffuse on the scenario by means of a simple average filter. The agents motion and the range of diffusion by the chemo-attractants are limited in the discretized plane. A time step in our system is finished when all available agents finish one decision in a random sequence. An agent's body occupies one grid and moves no more than one grid at each time step. The agent's sensor samples the chemo-attractants in the grid where the sensor locates. A sensor is a virtual device, which could coexist with other agent body or sensors in the same grid. The emergence pattern of the system is organized by the arrangement of agents' body.

A single agent is composed of three components, i.e. the left sensor, the right sensor and the main body as shown in Fig. 1. The length of the sensor arm is used to represent the distance between the sensor and the body of an agent. The sensor angle formed by the sensor arm and the forward orientation is fixed to 45° . Each sensor is armed with a Trail Sampling module and a Chemo-nutrient Sampling module, which are used to measure the trail and chemo-nutrient concentration of its grid, respectively. The Synthesis Comparator compares the synthetic weighted values of chemo-attractants sampled by the left sensor and the right sensor, and controls the agent to move toward the direction with larger value.

The Motion Counter is simple but effective to record the motion of an agent and balance the amount of the population. A new born agent initializes its motion counter as zero and chooses the forward direction from the eight usual geographical orientations randomly. At each time step, an agent attempts to move forward to the neighbor grid. If the neighbor grid is occupied by another agent, the agent stays at the current grid and changes its forward direction randomly and

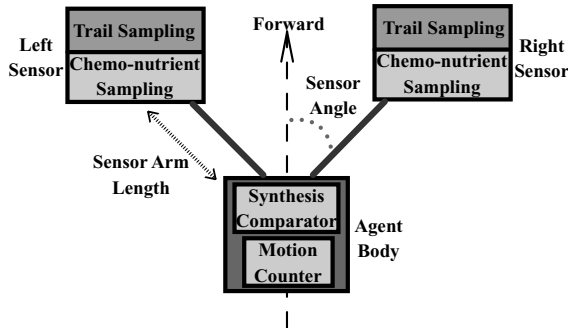


Fig. 1. The architecture and morphology of a single agent

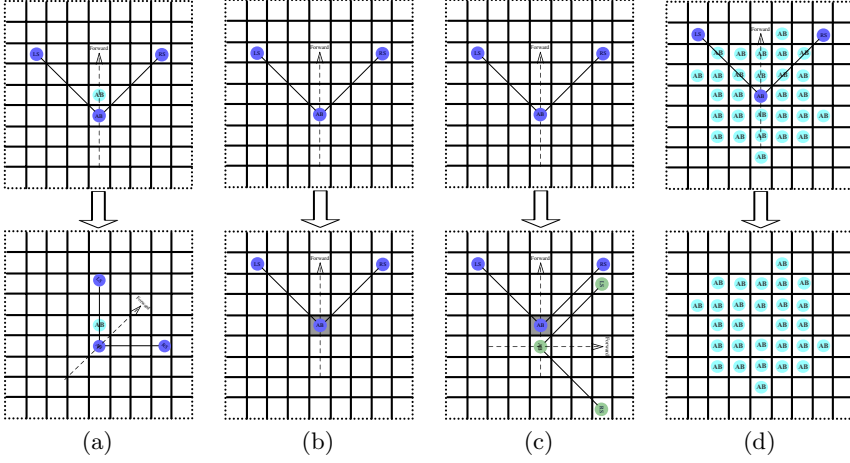


Fig. 2. Four situations that an agent (colored by sky-blue) might confront. (a) Failure to move forward. (b) Success to move forward. (c) Success to move forward and reproduction is triggered. (d) Elimination is triggered by reason of being immovable for a long time.

subtracts one from its Motion Counter. If the neighbor grid is empty, the agent moves to the grid, and deposits certain quantity of trail here, it also adds one to the Motion Counter and rotates to the direction with higher sense value. The number in Motion Counter quantifies the fitness of an agent. The larger the number in Motion Counter is, the more adaptable to the environment the agent is; otherwise, the agent is not fitted for the environment. In consequence, two values (RT and ET , see Table 1) are set to trigger the reproduction and the elimination of an agent. When the number in the Motion Counter is greater than RT , a child agent is born at the last grid where its father agent stayed. If the number is less than ET , the elimination is triggered and leads the forever disappearance of that agent. Fig. 2 gives examples how these situations may take place.

2.2 Basic Parameters of the System

Our enhanced system partially preserves the parameters presented in [13], but the last seven parameters in Table 1 are newly introduced. They are used to distinguish chemo-nutrient and trail, the diffusion and attenuation of chemo-nutrient, and achieve agents' evolution.

An agent calculates the actual value of the sampled chemo-attractant SV by the simple linear weighted method $SV = WT \times TV + WN \times NV$, in which TV and NV denote the trail value and nutrient value in the sensor's grid, respectively. WT and WN are the coefficients to distinguish the different influences of trail and nutrient. To emphasize the function of nutrient, WN is larger than WT . In the scenario, a food source has the shape of square and occupies 3×3 grids. The concentration of chemo-nutrient in these grids occupied by a food source is simulated by the parameter CN . The chemo-nutrient diffuses in the way of

Table 1. Basic parameter setting of the system

Parameter	Value	Explanation
Scenario Size	200×200 grids	The planar area for network formation
Initial Population Density	50%	Initially generating 200×200×50% agents in the scenario randomly
Sensor Arm Length	7 grids	The distance between sensor and its body
depT	5	The quantity of trail deposited by an agent
dampT	0.1	Diffusion damping factor of trail
filterT	3×3	The size of mean filter for trail
WT	0.4	The weight of trail value sensed by an agent's sensor
CN	10	The Chemo-Nutrient concentration of each Node
dampN	0.2	Diffusion damping factor of chemo-nutrient
filterN	5×5	The size of mean filter for chemo-nutrient
WN	1-WT	The weight of chemo-nutrient value sensed by an agent's sensor
RT	15	If the motion counter is greater than RT, the reproduction is triggered
ET	-10	If the motion counter is less than ET, the elimination is triggered

a 5×5 average filter that is a general smoothing operator in image processing. The damping factor $dampN$ controls the attenuation of chemo-nutrient. At each time step, chemo-nutrient in all grids excluding the food source grids updates simultaneously through that filter and decreases to $1 - dampN$ of the previous value. On fixed boundary condition, the system adopts zero as its boundary value. Those grids near the boundary of the scenario require the value to compute its new chemo-attractant through its corresponding filter. As mentioned in Section 2.1, RT and ET are used to maintain the number of agents. And they do not require precise adjustment, but too small values may lead to an unstable mesh-like pattern.

The length of sensor arm is the sampling distance of an agent. On fixed boundary condition, a sensor of an agent might reach out of the scenario. If the left sensor reaches out of the scenario, its agent chooses to turn right 45 degrees; Otherwise, it turns left. However if both sensors are out, its agent turns back. When the length of sensor arm is shorter than the diffusion distance of chemo-attractants, isolated mass may appear in final pattern.

2.3 The Pattern Formation and Population Evolution

After introducing the basic parameters in Table 1, we run the system without the inducing of any food source and observe its self-organized pattern and dynamic

population evolution on periodic boundary condition and on fixed boundary condition in this subsection. On either boundary condition, according to the setting of initial population density, 10,000 agents are generated randomly without positional conflict before running the system. Fig. 3 shows the snapshots images of the system running from initial state to stable on periodic boundary condition (Fig. 3(a)) and fixed boundary condition (Fig. 3(b)). A black pixel of Fig. 3 stands for an occupied grid.

In Fig. 3(a), the initial dense irregular little meshes gradually fuse into bigger ones, while the width of each edge is almost the same. Finally, the pattern is stable at the state with five connected straight line segments and without any mesh as shown in bottom middle of Fig. 3(a). By the same operation in [13], the final pattern is tiled to produce a bigger picture in bottom right. The obtained Honeycomb-like mesh here has some differences in angles and edge length from that of [13]. The 120 degrees are not found here, but a closer edge length ratio is observed. The ratio of angles (149.2 degrees vs 105.4 degrees) is 1.42 to 1, and the ratio of the edges length (146 grids vs 102 grids) is 1.43 to 1. The very close ratio of edge length and angle seems to indicate a possible relation between them in this pattern formed by this system.

The pattern formation on fixed boundary condition shown in Fig. 3(b), is significantly different from that on periodic boundary condition. In the stable state (bottom left), all meshes are closed but no strait line survives. The population of agents decreases with the system running. At last, several agents congregate to a little mass in the center of the scenario, which maintains a minimization area of the population. Even though the pattern being stable on the mass, the evolution mechanism of our system keeps both the population and generation dynamically.

The population density, expressing the scale of population, is defined as the percentage of the number of agents to that of grids in the scenario. It is an important feature of population structure. Three different initial population density, 1%, 50% and 90%, are chose to understand the influence of evolution mechanism to the population. Running the system for 20,000 time steps, the curves of the population density at each step on periodic and fixed boundary condition are

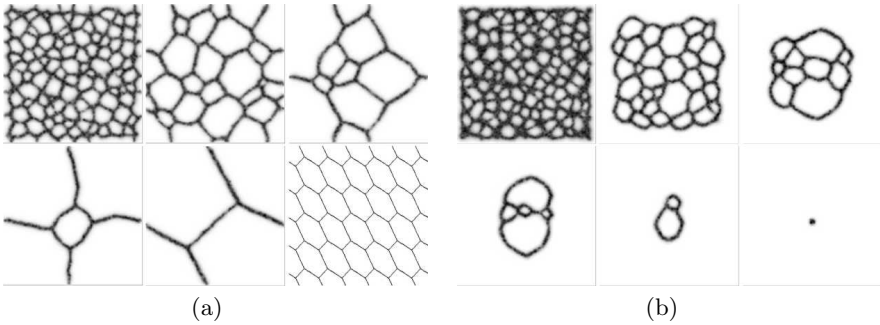


Fig. 3. Agent swarm self-organized progress on periodic and fixed boundary conditions

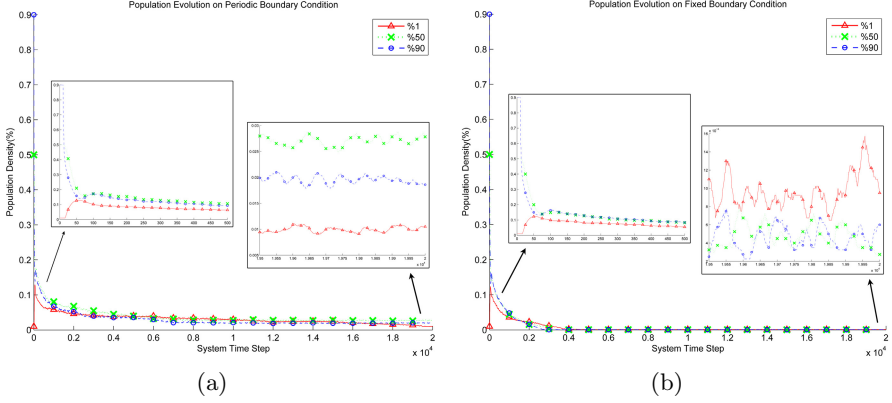


Fig. 4. The population evolutions on periodic and fixed boundary conditions with different initial population density

shown in Fig. 4(a) and 4(b). The three markers, the red delta, the green X and the blue circle in Fig. 4 present the initial population density of 1%, 50% and 90% respectively. The embedded subgraphs in both Fig. 4(a) and 4(b) amplify the detail in the first and last 500 time steps. During the first 500 steps, the three kind curves trend to close the line whose population density is equal to 10%, either suffering a rapid decrease or experiencing a slow increase. A fluctuation of population in a narrow range is observed in all curves in the last 500 steps. The fluctuation of each curve maintains its necessary and different amount of agents to guarantee the persistence of the pattern.

3 The Approximation of *Physarum* Transport Networks

This section describes the situation that all the parameters in Table 1 are used to run the system on fixed boundary condition for simulating the formation of *Physarum* transport networks. In biological experiments, there are two common methods to investigate the evolution of *Physarum* networks. One method is to use the organism of *Physarum* to cover the substrate as well as all food sources, such as in [1] and [2]. The other is inoculating the *Physarum* from one food source, which used in [6] and [10]. The designs of the numerical experiments in this section simulate both methods by consulting some distributions of food sources in those works and other datasets in [13] as well. The videos of all the experiments in this section are available online (http://www.tudou.com/home/_79693894).

3.1 Networks Formation from All Nodes Covered

During the approximation of *Physarum* networks, the scenario could be seen as the substrate cultured the *Physarum*, and the food sources as the nodes.

This section constructs RGB images to show the approximated networks. The purple spots in the images simulate food sources, and the green edges simulate protoplasmic tubes of *Physarum*. The value of Green channel represents the trail in the scenario, however the chemo-nutrient is mapping to both Red and Blue channels.

Fig. 5 shows the network formation of each data set by four images (1-4 from top to bottom) using the basic parameters in Table 1. Initially the randomly generated 20,000 agents cover exactly half grids of the scenario, which has an analogy to the methods using pieces of *Physarum* covering the available agar surface in [1]. By running the system within 20,000 steps, the network of every dataset will be stable as shown in the fourth image of each subfigure. In Fig. 5(a), the final network is analogous to Steiner's minimum tree (SMT) which is similar to the thick tubes of *Physarum* shown in [2]. The network formed by *Physarum* on the six food sources from [1] reveals a half SMT and half cycle-like pattern shown as Fig. 6(a). However the network formed on the same nodes distribution in [13] is of the only feature of SMT shown in Fig. 6(b). The network formation of the six nodes dataset in Fig. 5(b) of this paper, which seems to be a compromise between them, reveals a pattern of SMT on both sides of the nodes as well as a circle in the middle. The network formation in Fig. 5(c) shows a pattern of Delaunay triangulation network mentioned in [1], but the transitory unstable edges in the middle of the circle shown in the second and third images

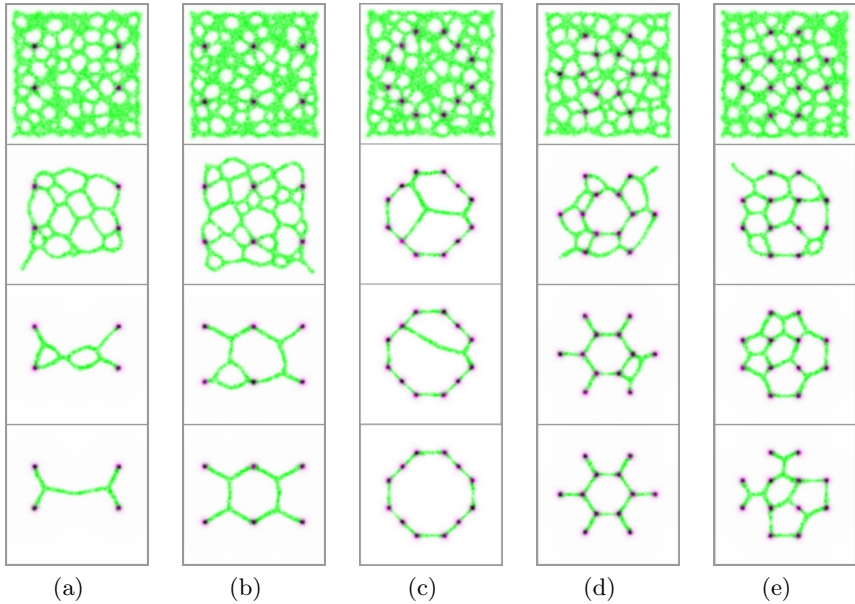


Fig. 5. Networks formation on various distributions of nodes completely following the parameters in Table 1. The time-line direction of these snapshots is from top to bottom, and the bottom image is the final stable pattern of each dataset.

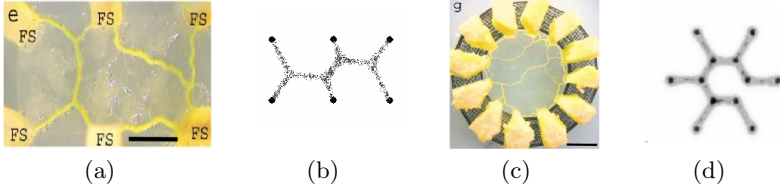


Fig. 6. Figures from [1] and [13] are used to compare with the networks of our system

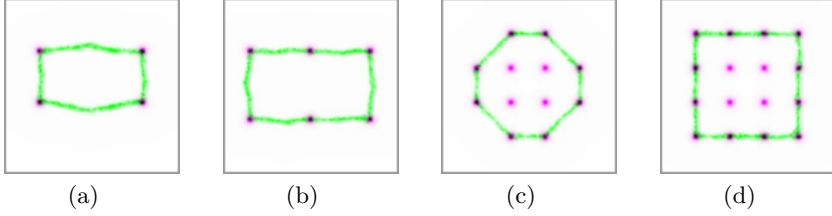


Fig. 7. Outer cycle network formation when the initial population set to 100%

of Fig. 5(c) is more close to the real network of *Physarum* shown in Fig. 6(c). Fig. 5(d) is very similar to that in [13] shown as Fig. 6(d), however ours forms a circle connected the inner nodes. The stable network shown in Fig. 5(e) manifests a more complex structure which blends both the properties of SMT and cycle.

For feather exploring the performance of the system presented in Section 2, we change some parameters to rerun this system on the datasets used above. If the initial population density is set to 100%, there is no empty grid for any agent move forward in this scenario. The population decreases suddenly as the evolution mechanism working, and some agents near the four bounds of the scenario can survive. Then those agents reproduce to form a closed ring and shrink to the center gradually until the ring is adsorb firmly by the outer nodes. That is the interesting pattern shown in Fig. 7. Nodes arrangement in Fig. 7(d) is the supplement of Fig. 7(c) to illustrate how the inner nodes are excluded by the outer cycle. The networks of data set in Fig. 5(c) and 5(d) under the parameter of 100% initial population density are not given because they have the same stable patterns to those in Fig. 5.

Furthermore the dataset, whose three nodes are locating at the vertices of an equilateral triangle, is chosen as the test of approximation. In Fig. 8, the upper of each subfigure is the network formed by our system and the lower is the similar *Physarum* network in [2]. When adopting the basic setting of the system, the SMT pattern formed to connected all the nodes as shown in Fig. 8(a). If the system sets a larger filterN to simulate a further distance of nutrient diffusion, the pattern called cycle (Fig. 8(b)) and analogue of SMT(Fig. 8(c) and 8(d)) in [2] could be observed. The last two patterns are not stable, both of them might transform to SMT. The results of numerical experiment and biological

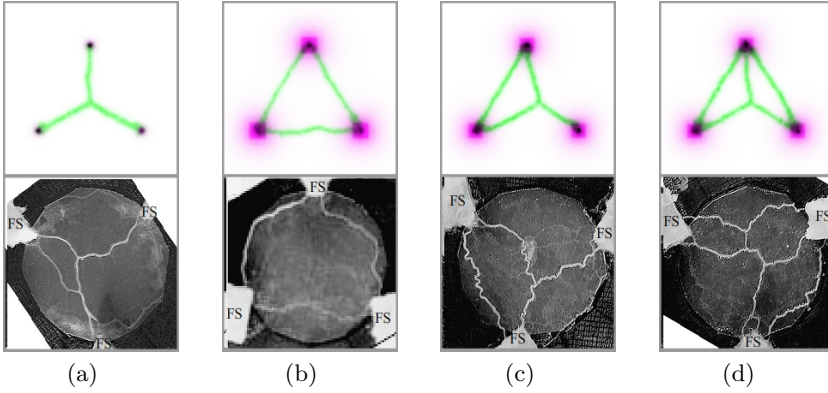


Fig. 8. Various networks formation of three nodes located at the vertices of an equilateral triangle. The upper subfigures are from our system and the lower ones from [2] (FS is short for Food Source). (a) uses the basic parameter setting. (b) changes the filterN to 19×19 . (c) and (d) change the filterN to 17×17 .

experiment illustrate the flexibility of our system to form various networks in the same dataset.

3.2 Networks Formation from One Covered Node

When cultured in a nutrient-rich substrate, *Physarum* propagates many branches of protoplasmic tubes. While in a nutrient-poor substrate, it propagates its pseudopodia cautiously to forage for food sources with fewer and tree-like tubes. In [10], a biological experiment is designed to investigate the spanning tree constructed in the nutrient-poor substrate. The distribution of food sources in that experiment is alike the nodes arrangement in the first image of Fig. 10. By inoculating the *Physarum* at the southern food source, the protoplasmic tubes construct a spanning tree of all food sources finally. In that work, the two-component Oregonator Model of BZ reaction is used to explain the building of the spanning tree. Fig. 9 quotes from [10]. The left image of Fig. shows the result of two-variable Oregonator Model after erosion operation on diffusion wave and the right one is the enhanced picture of *Physarum* constructing the spanning tree.

Inspired by that work, some changes are applied to the system in this paper to simulate the *Physarum*'s behavior to construct spanning tree in nutrient-poor substrate. Firstly, the parameters related to nutrient are adjusted to the suitable values to emphasize the importance of nodes and its gradient in a larger range. Thus these parameters CN , $filterN$, WN and WS are set to 20, 13×13 , 0.8 and 0.2, respectively. Secondly, 10 agents are generated manually at the grids of southern node and the system is set up. Then the population of agents develops and gradually covers all nodes. Finally the stable spanning tree is constructed, which is similar to the both trees constructed by the Oregonator Model and

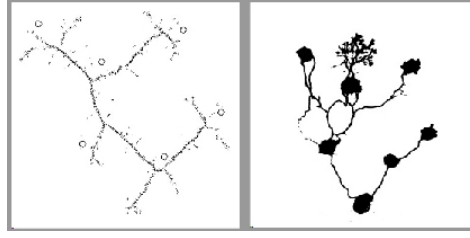


Fig. 9. The spanning trees constructed by Oregonator Model and *Physarum* from [10]

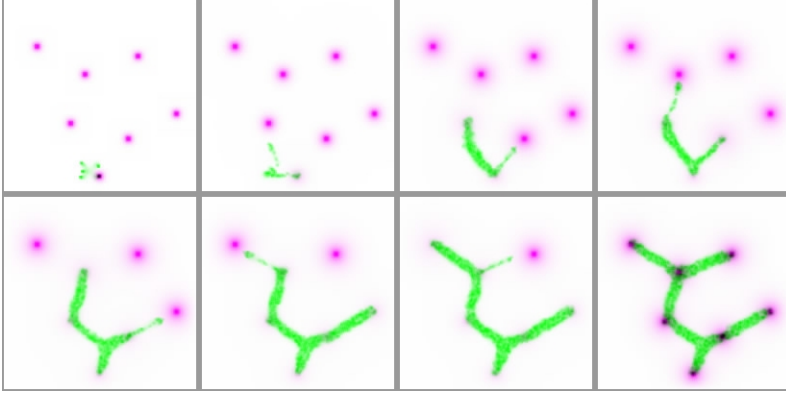


Fig. 10. The process of constructing spanning tree from top to bottom and left to right

the biological experiment in [10]. Fig. 10 records the process of the formation of spanning tree by this system.

4 Concluding Remarks

The enhanced Multi-agent system in this paper approximates the formation of *Physarum* networks in various distributions of food sources. In this system, the diffusion of chemical nutrient is independent from that of trail emitted by agents. Meanwhile, the number of sensors is decreased to two, but the function of a sensor is extended to sample both nutrient and trail. The most interesting point of this work is that the Motion Counter as a simple memory module of an agent achieves the complex evolution mechanism. It is a flexible and self-adjusted method to maintain the population to form a stable pattern, comparing with that of utilizing the local population density and probability.

The pattern formation and the variation of population in the system are observed on periodic and fixed boundary conditions. Then some datasets based on the food sources arrangement in biological experiments of other researchers are used to investigate the features of the networks formation by the system. Features, including SMT, cycle-like and spanning-tree, are found in these final

networks which are similar to the real networks constructed by *Physarum*. Future works for this system are to explore other possible patterns on various setting of parameters, the construction of efficient networks on more complex data sets and the feature of dynamical reconstruction of the system.

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