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A Multi-Robot Pattern Formation Algorithm Based on Distributed Swarm Intelligence

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Abstract—**This paper presents a solution to the problem of pattern formation on a grid map, for a homogeneous multi-robot system. In this paper we propose a natural swarm inspired algorithm based on the Particle Swarm Optimization (PSO) model and Virtual Pheromone mechanism. Basically, a virtual pheromone trail based method is proposed as the message passing mechanism among the robots, where robots make distributed movement decisions through local interactions. For one individual robot, there are two working modes, *exploration* and *dispersion*, with different indicators in the PSO model. By cooperating and communicating through the virtual pheromone, agents of the multi-robot system switch between the two working modes. The PSO method helps to allocate reasonable robots to different parts of the predefined pattern. A series of experiments on simulator is carried out and proves the convergence and excellent scalability of our algorithm. By optimizing some parameter in the PSO model with the help of the simulator, the efficiency of pattern formation is further improved.**

Keywords-multi-robot system; pattern formation; swarm intelligence; PSO; Virtual Pheromone

I. INTRODUCTION

Multi-robot pattern formation has received much attention in recent years, which can be the basement of some advanced application like multi-robot construction, collective movement, and cooperative transport. With the development of robotic technology, simpler and cheaper robots become available and coordination with large scale robots swarm becomes the trend of multi-robot applications. Some centralized coordination based algorithms meet their bottleneck in this large scale scenario, including the Behavior-Based Allocation [1], Market-Based Coordination [2, 3 and 4] and etc. As the agent number increases, the communication cost in negotiation and the computation cost in optimization [5] increase dramatically, making the complexity of scheduling rise and the efficiency of these algorithms drop significantly.

To solve this problem, some bio-inspired swarm intelligence based approaches were proposed. In the swarm intelligence based multi-robot pattern formation the pattern to be formed is dictated by the environment. At the same time, the geometrical shape or size of the final patterns formed is partially determined by the task at hand of each agent during the coordination. In natural swarms, the surrounding of a prey by a group of predators or the formation of pulling chains by weaver ants can be considered as examples of multi-agent pattern formation.

In this paper, we proposed an approach relying on the robots themselves to make decisions instead of a centralized coordinator. The communication and coordination among the robots are realized through the Virtual Pheromone Model [6] and a modified Particle Swarm Optimization (PSO) algorithm [7]. Without centralized coordination, the multi-robot system works in a complete distribution mode, using the local environmental information and virtual pheromone to allocate tasks among the robots. Basically, each robot has two working modes during the task: *exploration* and *dispersion*. Initially, the grid-based map is divided into sub-areas with some grids noted as the predefined pattern. In the *exploration* working mode, the robot compute its optimized target sub-area which contents noted grids, basing on the virtual pheromone given by other robots, to find the nearest sub-area in which the least robots already move, and make the movement basing on PSO model. Once reaching the targeted sub-area, it turns into the *dispersion* working mode to allocate itself on a certain noted grid. With this swarm intelligence based approach, the multi-robot system can form the predefined pattern in an effective and scalable way.

The paper is organized as follows: Section 2 introduces the related works on multi-robot pattern formation and swarm intelligence based applications. Section 3 offers some preliminaries, including the world definition and the problem statement. Section 4 presents the virtual pheromone model and the PSO algorithm for the multi-robot pattern formation. Section 5 presents the simulation results on a C-based simulator platform. To conclude the paper, Section 6 outlines the research conclusions and future works.

II. RELATED WORKS

Gradient descent based techniques for motion control (including pattern formation) of small multi-robots systems have been studied in the past few years [8, 9 and 10], but without considering the pattern formation of synthesizing specific shapes. A modified approach is presented in [11], where a large group of robots generate patterns specified by implicit functions. The robots converge to a given 2D curve by gradient descent and spread along this curve by introducing repulsive forces. In this case the robots are able to converge to certain shapes (according to the predefined curve). However, the patterns that can be formed are limited to 2D curves and they are

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not formed in a scalable way. The mechanism to spread the robots along the curve is also relatively simple.

Chen and Chu proposed an attractive-repulsive interactions model for a multi-robot system to realize pattern formations in [12]. The interactions among the agents are assumed to be universally repulsive and selectively attractive, so as to form desired pattern in the system. By choosing appropriate coupling topologies, the multi-robot system can form most symmetric patterns and some asymmetric ones.

In this paper, we introduce a natural swarm inspired method into the Multi-Robot Pattern Formation problem, trying to enable the multi-robot system to form synthesizing specific shapes in a scalable way.

The area of natural swarm inspired motion control for multi-robots systems has been very active in the recent years. One of the first works dealing with the motion control of large groups of agents was done by Reynolds in his research of bird flocks (called boids) [13]. With some simple motion rules that each individual member follows, the whole flock can represent some complicate motions, like dispersion, aggregation and obstacle avoidance. Kennedy and Eberhart introduced this idea into the optimization computation in 1995 and named this model Particle Swarm Optimization (PSO) [14]. PSO emphasizes the collaboration among individuals. In this algorithm, system is composed by a swarm of particles, each stands one possible solution. These particles get initialized to a group of random solutions, and then start searching process, following the global optimal particle and finally achieve global optimization [14]. Kennedy and Eberhart proved the efficiency, convergence and robustness of PSO [15].

Yan and Jing introduced this natural swarm inspired method into multi-robots coordination to accomplish a construction task [16]. A multi-robot system searches for randomly distributed blocks and pushes those blocks to predefined locations. Basically they use a virtual pheromone trail based method as the message passing mechanism among the robots, along with a modified Particle Swarm Optimization (PSO) method for task allocation between the robots. Robots used the virtual pheromone and the distance to the target to calculate the indicator in PSO model. The robot in selecting phase used this indicator to make decision of the target block. According to the limited communication scope, the author simplified the PSO model without considering the affect of global optimal value, only with local optimal value.

In our previous work [17], we designed a relatively simple mechanism to coordinate a small sized multi0robot system to form some patterns and performed some initial experiments using a group of self-designed robot. To realize the pattern formation by large-scale multi-robot system, two major modification are made to the PSO model in our work: first, we adopt the virtual pheromone based methods that is similar to [16] as the message passing and task allocating mechanism, with modified pheromone model to prevent the overflow of received pheromone; second, each robot has two different working modes with different PSO models to guarantee the system performance.

III. PRELIMINARIES

A. World Definition

We assume that the multi-robot system moves in an $M \times N$ grid-based map. To reduce the computational complexity, the map is divided into $m \times n$ sub-areas, where each sub-area consists of equal number of grids. Each agent of the multi-robot system stores an $M \times N$ matrix G with the element g_{ij} recording the predefined pattern. This matrix can be represented as follows:

$$g_{ij} = \begin{cases} 1, \textit{for the grid in the predefined pattern} \\ 0, \textit{for the grid out of the predefined pattern} \end{cases} \quad (3\text{-}1)$$

The agents will spread on the predefined pattern evenly through a PSO-based searching method, with the help of the virtual pheromone. The pheromone information s is updated by the agents based on their local information.

There are several assumptions for the agents of this multi-robot system, which are quite reasonable in the real applications: (1) All agents are anonymous and homogenous which cannot be distinguished by their appearance; (2) The communication scope of a single agent is limited; (3) The localization and movement of agents are accurate and the movement of agents could be measured in grid, the basic unit of the map; (4) Collisions between agents and agents to obstacles are negligible.

B. Problem Statement

Given a pattern $F = (q_1, \ldots, q_n)$ on the grid (a collection of coordinates, in our case, the pattern is defined with the help of equation 3-1), the Formation Problem is the problem of finding a distributed algorithm, such that from any initial distribution of the agents, they will eventually spread themselves in the desired pattern F.

In a multi-robot pattern formation problem, there is an unknown area with a predefined pattern. The randomly distributed swarm coordinates to search this area for the coordinates that constitute the pattern and finally finishes spreading in the collection of coordinates and forming the desired pattern. The target of our work is to develop a scalable coordination algorithm with which the whole multi-robot system can form the predefined pattern with the time cost as low as possible.

IV. PATTERN FORMATION ALGORITHM

Initially, certain grids of the map are noted to be the predefined pattern with the information stored in the matrix G and all the robots are located randomly on the map. Because of the robots' random distribution, the search for noted grids starts from the local search. Thus, the robots are firstly set to the *dispersion* working mode, trying to find an unoccupied noted grid. In this mode, the individual agent shares the grid information of the local sub-area with its neighbors through a virtual pheromone mechanism to distributed incremental learning. A PSO based searching method is applied for local task allocation among robots, using pheromone information and the distance value between grids as the indicator, to calculate the decision of next movement.

If no unoccupied noted grid exists in this sub-area, the robot labels the sub-area as vacant and turns into the *exploration* working mode. In this mode the robot also makes use of the pheromone information along with the distance value between sub-areas to calculate the decision of next movement through the PSO method, in order to find a nearby non-vacant sub-area with fewer robots already in it.

This process keeps going on until all the robots disperse on noted grids and the pattern defined by these noted grids is thus formed by the robotic swarm.

A. Virtual Pheromone

In order to ensure the efficiency of coordination between robots and to avoid the robots' concentration in some part of the pattern, we introduced a bio-oriented virtual pheromone model similarly to [16]. Initially the virtual pheromone density is set to be 0. To emulate the enhancement procedure of pheromone in nature, whenever a robot finds an unoccupied noted grid, it would update the pheromone density and broadcast this information to its nearby neighbors. Because of the large scale of the swarm, an upper bound of pheromone density is set to avoid overflow. Also, the virtual pheromone density will be eliminated over time.

More specifically, we consider an actuated robot r, the virtual pheromone density of a certain sub-area *(i, j)* for robot r at the time t can be presented as follow:

$$\tau_{ij}(t) = (1-\alpha)\tau_{ij}(t-1) + c\sum_{k=0}^{N_r}\Delta\tau_k \qquad (4\text{-}1)$$

Where α is the attenuation parameter, $\Delta\tau_k$ is the pheromone updated from the neighbor robot k that stays in the communication scope of robot r, c is the accumulate parameter, where $0<\alpha<1$ and $0<c<1$. Each robot maintains an $m\times n$ pheromone matrix P with the element of τ_{ij}. The first term of equation (4-1) is used for pheromone elimination and the second term is used for pheromone enhancement.

When the robot runs in a certain sub-area *(i, j)* in dispersion mode, it also maintains a similar matrix P' to store the pheromone density information for each grids of this sub-area. Thus the virtual pheromone can not only help the robot to identify the sub-areas which fewer robots already interested in to realize even dispersion, but also efficiently lead the robot to the grids that are most possible the noted ones based on previous knowledge.

B. PSO based movement decision

In our approach, the robots use a PSO based searching method to make movement decisions. The next movement a robot would make is defined by the equations as follow:

$$\begin{aligned} v_{id}(t+1) = {} & w\times v_{id}(t) \\ & + c_1\times rand()\times\left(p_{ld}(t)-x_{id}(t)\right) \\ & + c_2\times rand()\times(p_{gd}(t)-x_{id}(t)) \end{aligned} \qquad (4\text{-}2)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (4\text{-}3)$$

$1\le i\le N,\ 1\le d\le D$

Where $v_{id}(t)$ is the velocity of robot *i* on the d^{th} dimension, $p_{ld}(t)$ is the local optimal position, $p_{gd}(t)$ is the global optimal position, c_1 and c_2 are the accelerate factors, w is the inertia factor, $x_{id}(t)$ is the position of robot *i* on the d^{th} dimension. The choice of the constant factors affects the efficiency of the searching.

In the *exploration* working mode, the robots broadcast their pheromone matrices and receive the pheromone matrices to update the ones of their own. The individual robot *r* uses its updated pheromone matrix and calculates the indicator function:

$$I_{ij}^r(t) = \frac{e^{-\tau_{ij}^r(t)}}{d_{ij}^r(t)} \qquad (4\text{-}4)$$

Where $d_{ij}^r(t)$ is the distance from robot r to the center of sub-area *(i ,j)*. The robot uses this indicator to find the global optimal target sub-area with the max indicator value, and then puts it into the modified PSO model:

$$\begin{aligned} v_{id}(t+1) = {} & w\times v_{id}(t) \\ & + c_2\times rand()\times(p_{gd}(t)-x_{id}(t)) \end{aligned} \qquad (4\text{-}5)$$

In the *dispersion* working mode, the robots broadcast their local sub-area pheromone matrices P' and receive the update from their neighbors. The individual robot r reads its updated P' matrix and calculates the indicator function

$$I'^r_{ij}(t) = \frac{e^{\tau'^r_{ij}(t)}}{d'^r_{ij}(t)} \qquad (4\text{-}6)$$

Where $d'^r_{ij}(t)$ is the distance from robot r to the grid *(i, j)*. The robot uses this indicator to find the global optimal target grid with the max indicator value, and then puts it into the modified PSO model:

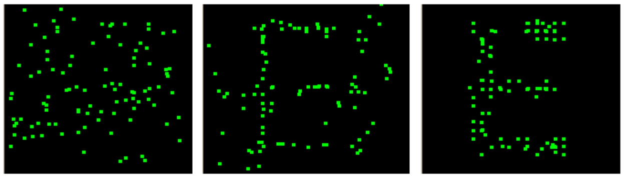
$$\begin{aligned} v_{id}(t+1) = {} & w\times v_{id}(t) \\ & + c_1\times rand()\times\left(p_{ld}(t)-x_{id}(t)\right) \end{aligned} \qquad (4\text{-}7)$$

After the calculation of velocity, the robot makes its movement decision according to the formula 4-3 to continue the search for noted grids.

V. SIMULATION

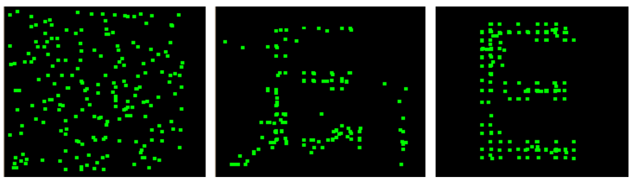
To demonstrate our approach, we designed a simulator and performed several simulations with a large number of robots for different patterns to test the algorithm's efficiency and scalability. We also used this simulator to help to improve the algorithm by adjusting some constant parameters. In these simulations, the size of map is set to 200×200 grids. The map is divided into 20×20 sub-areas and each of the sub-area gets the size of 10×10 grids. The time unit of the simulator is the atomic unit of agent's movement. That is, in one time unit, the robot can make one movement decision by broadcasting and receiving information.

We first simulated the pattern formation of the letters E. Figure 1 shows the snapshots of the simulation for a multi-robot system with 100 agents. Figure 2 shows the formation of the same letters but with 200 agents.



0% accomplished *50% accomplished* *100% accomplished*

Figure 1. 100-agent pattern formation, green spots stands for the robots.



0% accomplished *50% accomplished* *100% accomplished*

Figure 2. 200-agent pattern formation, green spots stands for the robots.

Figure 3 shows the accomplishment percentage in the process of forming letter E with different swarm scales. We set the attenuation constant in the virtual pheromone model (Equation 4-1) to 0.1, the accelerate parameter in PSO to 1 .0 (Equation 4-2) and the inertia parameter to 0.6. From the figure we can find the accomplishment will reach 100% with the process going on. From Figure 3 we can see that the curves reach 95 % at an early time in the process. This figure also indicates that the swarm intelligence based approach has a good scalability.

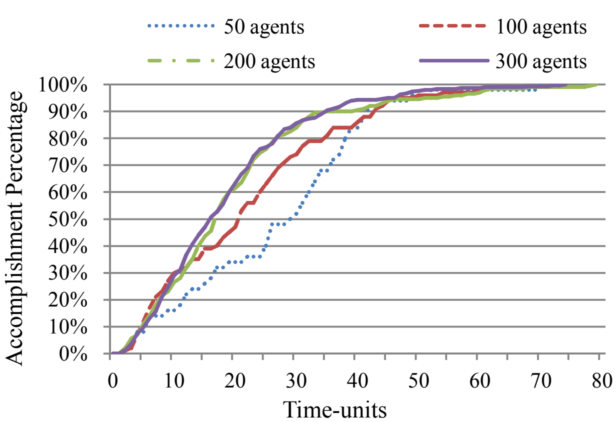


Figure 3. The convergence of accomplishment with different scales of the multi-robot system.

The parameters in the virtual pheromone model and the PSO model affect the efficiency of our algorithm. To evaluate their impact and improve our algorithm, we carry out a series of evaluation with different parameter values. Figure 4 shows the impact of attenuation factor in virtual pheromone model. It indicates that when the attenuation is higher, the time cost of the last 5% accomplishment is longer, which can be explained that the swarm with less coordination may performs worse in the end with less pheromone indications. Figure 5 shows the impact of inertia factor in PSO model. It indicates that the PSO model with lower or higher inertia factor does not work well. It can be explained that the inertia factor decides the maintenance of historic velocity, which affects the depth and breadth of the research. To keep a better balance between these two dimensions and improve the efficiency of our algorithm, an appropriate inertia factor is necessary.

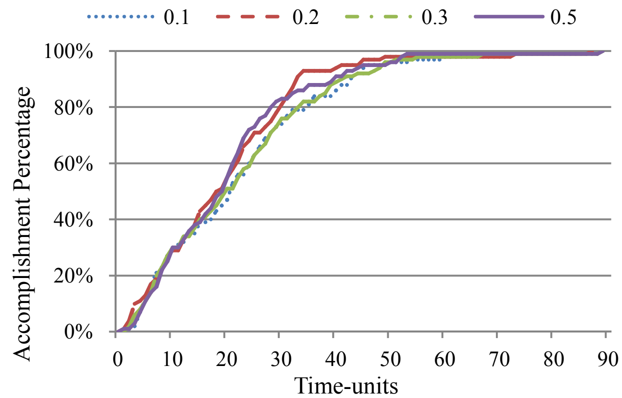


Figure 4. The impact of attenuation factor in virtual pheromone model.

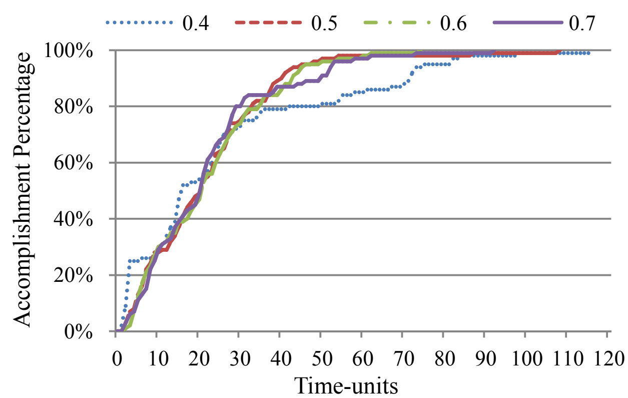


Figure 5. The impact of inertia factor in PSO model.

VI. CONCLUSION

This paper presented a swarm intelligence based algorithm for controlling a distributed homogeneous multi-robot system to synthesize specific predefined shapes. The proposed algorithm aims to reduce the random movement of robots, dynamically allocate the robots on predefined grids of the map to form specific patterns. The virtual pheromone method offers an effective coordination mechanism and works as a communication tool among the agents. The movement based on a modified PSO model ensures the efficiency of the pattern formation. Simulation was used to validate this algorithm and to evaluate its performance. The simulator was also used to help choosing the appropriate factors of the algorithm to get an improved performance.

Our future work will include a further study of this algorithm with more considering of the real-world environmental elements like collision avoidance, and a real world application on a hardware platform of swarm robots with the help of the simulator.

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