# Adaptive Potential Fields Model for Solving Distributed Area Coverage Problem in Swarm Robotics

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**Abstract.** Complete coverage of a given region has become a fundamental problem addressed in the field of swarm robots. Currently available approaches to the coverage problem are typically of computational complexity, and are manually specified with different map settings, which are not scalable and flexible. To address these shortcomings, this paper describes an efficient distributed approach based on potential fields method and self-adaptive control. It makes no assumptions about prior knowledge on global map, and need few manual intervention during execution. Although the motion policy of each robot is very simple, efficient coverage behavior is achieved at team level. We evaluate the approach against a traditional rule-based method and pheromone method under different target area scenarios. It shows state-of-the-art performance, both in the percentage of coverage and the degree of connectivity.

**Keywords:** Swarm robotics · Distributed area coverage problem · Potential fields · Adaptive control

## 1 Introduction

In recent years, there has been a rapid growth of progress in Swarm Robotics. Past works have demonstrated that using a team of less complex robots to solve tasks in a distributed manner is more efficient than using a sophisticated, well-designed individual agent [3,12,16]. Many applications of swarm robots require them to disperse and cover throughout their environments, such as exploration [8], surveillance [14], patrolling [2], and multiple target searching [7,17]. The coverage task is usually used as a sub-task of more complex activities. Triggered by these interests, area coverage problem today has became an attractive topic in swarm robotics research, which is considered to be highly relevant in practical applications.

In the absence of any centralized control, it is often challenging to monitor the system's global behavior when using swarm-based approaches. In this paper,


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we concentrate on the problem of distributed coverage of an unknown environment using a swarm of mobile robots. What we are interested in, is how the robots can disperse in a distributed, self-organised way. We propose a motion policy based on adaptive potential fields method, which doesn't need manual intervention (e.g. parameter tuning) when executing in a real scenario. The policy also maximizes the use of potential information from nearby robots within a local communication.

This paper is organized as follows. We start by discussing previous work in Sect. 2. In Sect. 3, we introduce the distributed area coverage problem and several definitions. We describe the details of the adaptive potential fields model in Sect. 4, and show the experimental results and discussions in Sect. 5. Finally, we conclude in Sect. 6.

## 2 Related Work

Conventional approaches for distributed coverage are realized with large robots that have considerable computation and memory capabilities on-board. A common feature underlying almost all these approaches is that they do not assume any limitations of the robots while executing the coverage task. A large number of these algorithms also assume that robots have a priori information about the environment [4,5,13]. Some researchers have obtained theoretical results for the coverage time and redundancy for multi-robot coverage problems [1]. However, no information about these parameters is provided in these papers.

Besides, several researchers have used swarming techniques to achieve distributed area coverage with multiple robots. A common feature of these swarm-based coverage algorithms is that they require localization capabilities on the robots to enable them to record or remember locations that are already covered. [15] describes ant-inspired heuristics for distributed area coverage. The environment is decomposed into cells using a grid and robots deposit virtual pheromone when visiting a cell. [9] defines four basic motion behaviours (random walk, wall following, avoiding all obstacles, and avoiding other robots), and designs a mechanism to switch between the four behaviours to maximize the area coverage.

## 3 Problem Formulation

In this section, we'll introduce the distributed area coverage problem and several definitions. In the area coverage task, swarm members must position themselves away from one another, with the objective of maximizing the area covered globally by the swarm. Also, the degree of swarm connectivity [6] should be minimized. We evaluate the effect of algorithms in these two metrics. This section defines and clarifies some key terms which are relevant to this intention and idea, and will be used throughout this article.

- **Environment**: A screenshot of the area coverage problem at the beginning of a simulation is shown in Fig. 1. $M \subset \mathbb{R}^2$ is an allowable environment area. We assume the robots have no priori information about the environment in advance, which requires exploration. We also assume the coverage area is an enclosed space.
- **Robot**: We use the foot-bot model defined in [10]. The foot-bot is a ground-based robot that moves with a combination of wheels and tracks. It is also equipped with numerous sensors and actuators.
- **Sensor**: The foot-bots can communicate with each other through a *range-and-bearing communication device* [10,11], allowing robots in line-of-sight to exchange messages within a limited range. Also, the robots are equipped with proximity sensors on board, which can detect objects around the robots.
- **Motion Policy**: The motion policy tells a robot what to do at each iteration. Therefore, when a robot detects the objects (obstacles or wall) and gathers information from other robots, it will decide what to do next based on motion policy.
- **Coverage**: We consider an environment to be covered as a condition that every place can be detected by at least one robot. Therefore, the motion policy should guide the robots in a way that their territory intersections decrease as time passes, but keep it in an ideal distance in order to communicate with each other. Different from [2], where each robot patrols by moving on the territory border when the full coverage is achieved, here we consider a static final state.

To conclude, we give a full definition of approximate distributed swarm robotics distributed coverage problem based on all the terms above.

**Definition 1.** *Approximate Swarm Robotics Distributed Area Coverage Problem:*

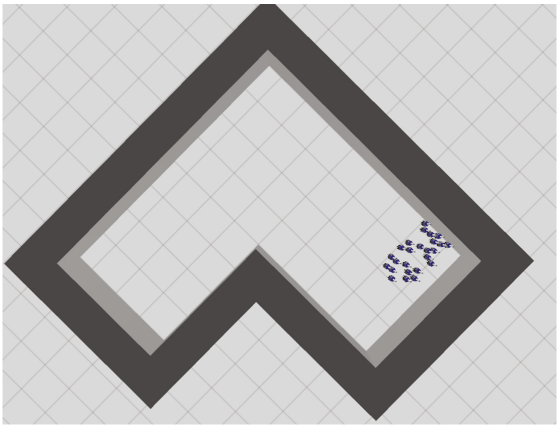


**Fig. 1.** A screenshot of the problem at the beginning of a simulation.

Given a set of $R$ robots, with communication radius $c_r$ and local communication graph $g_r$ in an initially unknown environment, find a set of actions $a_r^1, a_r^2, ..., a_r^T$ to be performed by each robot $r \in R$ based on the motion policy, such that the maximum complete coverage criterion is satisfied: $\max \bigcup_{r\in R} \bigcup_{t=1...T} c_r^t$ and the degree of connectivity is minimized: $\min \bigcap_{r\in R} \bigcap_{t=1...T} g_r^t$.

## 4 Adaptive Potential Fields Model

In this section, the main method of this paper is presented. Particularly, we first introduce a mathematically simple model used in molecules mechanics, which we find convenient to model the interactive virtual force between robots. Next, we design an adaptive control policy upon the potential parameter, which does not need any manual intervention while the coverage task is executing.

### 4.1 Lennard-Jones Potential Fields

The Lennard-Jones potential (also termed the L-J Potential) is a mathematically simple model that approximates the interaction between a pair of neutral atoms or molecules. The most common expression of the L-J potential is:

$$V_{LJ}(\rho) = \varepsilon[(\frac{\delta}{\rho})^{12} - 2(\frac{\delta}{\rho})^{6}]. \tag{1}$$

from which we can derive the force:

$$F_{LJ}(\rho) = -\nabla V_{LJ}(\rho) = -\frac{12\varepsilon}{\rho}[(\frac{\delta}{\rho})^{12} - (\frac{\delta}{\rho})^{6}]. \tag{2}$$

where $\varepsilon$ is the depth of the potential well, $\delta$ is the distance at which the potential reaches its minimum, and $\rho$ is the distance between particles. The reasons why we choose the LJ-Potential Fields to model the interactive force are mainly in three aspects:

- Easy calculated. The robots only need to query its sensory data and calculate the joint force.
- Connectivity maintenance. When the distance between two robots exceeds a certain value, the traction effect appears, which is beneficial to the maintenance of connectivity degree.
- Pattern formation. The artificial virtual potential field methods are widely used in the pattern formation tasks in swarm robotics systems, and it contributes to cooperative execution between robots when in an emergency.

### 4.2 Guided Growth Potential Field Model

When the entire swarm system reaches a stable state, namely the distance between each two robots is kept in stationary, they are not guaranteed to be fully covered in the target area, such as Fig. 2. Therefore, we propose a "guided growth" method similar to [8], but combined with the LJ-Potential model and adaptive control. We call it Guided Growth Potential Field method (GGPF). The key issues are as follows:

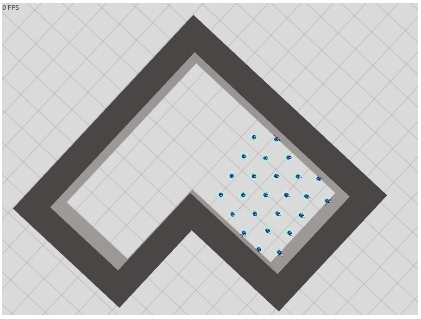


**Fig. 2.** Partially covered example

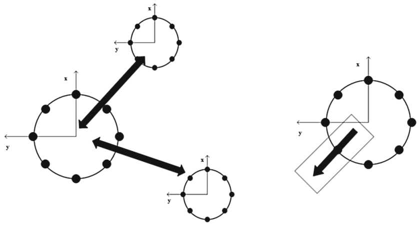


**Fig. 3.** A local vector graph

- **Local vector graph**. For each robot, when its local potential force tends to become zero, it'll construct a local vector graph as Fig. 3 shows. The local graph contains all the entities detected via the proximity sensors on-board. If the population is not enough to cover the entire area, the local vector graph may not be balanced from the geometric configuration view as Fig. 3.
- **Guided balance force**. We define the balance force as the supplementary of the joint LJ-Potential force in the local vector graph, which makes robot's velocity vector zero. The angle of the balance force can be calculated as:

$$\theta = atan\frac{-F_y}{-F_x}, \tag{3}$$

  in which the $F_x$ and $F_y$ are the joint force decomposed into x-axis and y-axis respectively. The robots on edge of the swarm system start to move away to explore uncovered area and doing so "pulls" the entire swarm because the other robots will follow the exploring robots in order to keep the potential field defined by formula 1. Thus the connectivity is kept.
- **Adaptive control of potential parameter**. The parameter $\delta$ in formula 2 determines where the potential reaches its minimum. It surely has an impact on the position where the interactive force becomes zero as well. When the balance force is applied to a robot, which means a "pull" effect is applied to the entire swarm, a constant will be added to $\delta$. This will make the potential fields expanding until all robots extend to the entire target area. When the balance force is near zero, it will be reduced in turn. This is the core of the adaptive mechanism in the guided growth model.
- **Information sharing via sensing**. For each iteration when executing, robot shares its potential information ($\delta$) through range and bearing sensor, and collects all the potential parameter $\delta_i$ from the neighborhood robots. It will adjust its $\delta$ with the average. This also embodies the essence of cooperation between robots.
- **Energy Decay**. In experiments, we have found an oscillation effect emerged in swarm robotics system when all robots fully cover the target area, due to the fact that potential energy converted to kinetic energy. We just add an

energy decay to the velocity of robots to make it stable, and it really performs well in simulation.

To conclude, a brief description of the proposed algorithm is shown in Algorithm 1.

**Algorithm 1.** Guided Growth Potential Field Model

**Input**: $\delta_i^0$: Potential parameter value for each robot $r_i$;
$\epsilon_1, \epsilon_2$: judgement for adaptive control;
decay factor

**for** *each* $r_i$ *in timestep* $t$ **do**
  **Loop**
    Gather Sensor information $(d_0^t, \theta_0^t, \delta_0^t), ..., (d_N^t, \theta_N^t, \delta_N^t)$;
    Get new potential parameter $\delta_i^{t+1} : average_{j=1...N}(\delta_j^t)$;
    Update joint LJ-Potential force $\overrightarrow{F_{i\_LJ}^t}$ with formula 2;
    Construct local vector graph $G_i^t$ and guided balance force $\overrightarrow{F_{i\_BL}^t}$;
    Calculate $\Delta x_i^t = (\overrightarrow{F_{i\_LJ}^t} + \overrightarrow{F_{i\_BL}^t})_x$; $\Delta y_i^t = (\overrightarrow{F_{i\_LJ}^t} + \overrightarrow{F_{i\_BL}^t})_y$;
  **if** $\|\Delta x_i^t\|^2 + \|\Delta y_i^t\|^2 < \epsilon_1$ **then**
    $\delta_i^{t+1} -= constant$
  **else**
    $\delta_i^{t+1} += constant$
  **if** $\overrightarrow{F_{i\_BL}^t} < \epsilon_2$ **then**
    $\Delta x_i^t * = decay$; $\Delta y_i^t * = decay$

## 5 Simulation Results and Discussions

In this section, we demonstrate the GGPF algorithm on simulation experiments. We have used the ARGoS [10] robot simulation platform for our simulations. ARGoS is a multi-physics robot simulator. It can simulate large-scale swarms of robots of any kind efficiently. We use the foot-bot model to perform the experiments and verify the algorithm. All the experimental scenarios are random generated with identical members, and the swarm robots know nothing about global information. In our experiment scenario, robots are initialized in a corner of an obstacle-free field and disperse according to the motion policy defined above. Each test is repeated for 20 times with 20 random closed maps with random obstacles, and the default number of robots is 25. Moreover, we pay careful attention to the percentage covered and the degree of swarm connectivity, with the variation of map size.

### 5.1 Algorithms for Comparison

Two algorithms are chosen for comparison, which are Rule-based Random Walk (RBRW) [9], and Ant-Robot Node Counting (ARNC) [15]. The RBRW algorithm defines four basic motion behaviours (random walk, wall following, avoiding all obstacles, and avoiding other robots), and designs a mechanism to switch between the four behaviours to maximize the area coverage. The ARNC algorithm devises the Ant-Colony Optimization (ACO) algorithm, where robots drop evaporating pheromone along their path, and when choosing their walking path give precedence to areas with the lowest pheromone level.

## 5.2 Simulation Results and Discussion

We first verify the scalability and self-adaption of the GGPF algorithm. As shown in Fig. 4, this set of simulation records one robot's potential parameter $\delta$ as the iteration increases. The map size is set to 100, which is relatively large compared with the swarm population. Figure 4 confirms our prediction in Sect. 4.2, that as the swarm expands, the potential parameter $\delta$ will decrease after robots reaching the edge of the target area. It is intuitively clear the entire swarm system has the dynamic perception to the target area, and it doesn't need any manual intervention of parameter tuning during the policy execution. When the local vector map of a robot is balanced, the information will spread to the inside, and finally the entire swarm remains stable persistently.

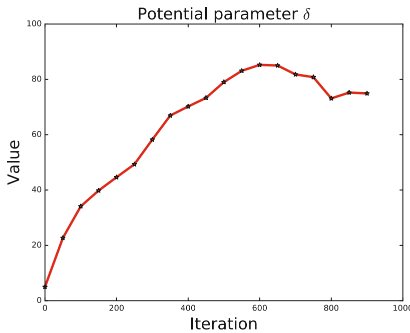
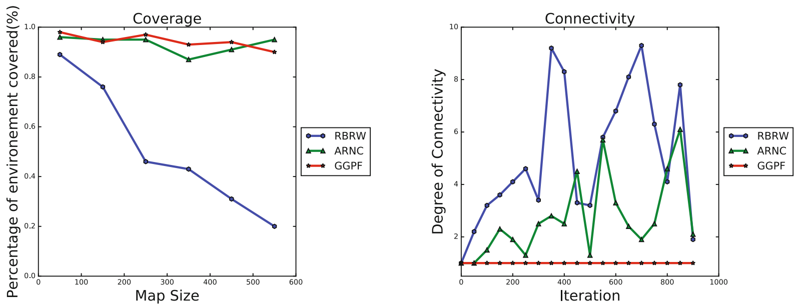



**Fig. 4.** The evolution of potential parameter $\delta$.

The performance of percentage covered with the variation of map size is shown in Fig. 5a. The RBRW algorithm performs very poorly as the map size increases, and only achieves good performance when the target area is crowded. This is reasonable because of the total absence of coordination among the robots. The connectivity performance is also bad because robots will leave each other when they are get closer (Fig. 5b). The pheromone-based algorithm performs well in percentage of coverage, indicating that the pheromone information is useful for coverage task. But it also performs poorly with swarm connectivity. This is because each robot selects its path only depending on the pheromone value of the local position. A robot tends to choose the direction with rare pheromone, and thus breaking the integrity of swarm connectivity.

Our method, combining the potential fields method with guided balance force outperforms the other two algorithms. Robots will detect the edge of the target




(a) Percentage of environment covered (b) Degree of connectivity

**Fig. 5.** Simulation results

area, and expand the coverage through implicit communication. Each robot in close proximity of other robots is repelled by nearby entities until its local communication graph is balanced. The percentage of environment covered is always high, as the map size increases. Meanwhile, with the limitation of potential field, the distance between each two robots is kept in a range controlled by the potential parameter $\delta$. As a result of that, the degree of connectivity is always one, which is beneficial to other tasks execution of the swarm system.

## 6 Conclusion

Complete coverage of a given region has become a fundamental problem addressed in the field of swarm robots. This article addressed the distributed coverage problem in unknown environments using swarm robotics, and proposed a motion policy based on adaptive potential fields method. The policy doesn't need manual intervention (e.g. parameter tuning) and maximizes the use of potential information gathering from nearby robots within a local communication. Experimental results showed that the adaptive potential field based algorithm is efficient and is superior to a rule-based random walk approach and pheromone method under different scenarios.

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