An Adaptive Stigmergic Coverage Approach for Robot Teams

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Abstract

In this paper, an adaptive multi-robot coverage approach called **A-StiCo** (for "Adaptive Stigmergic Coverage") is described. According to **A-StiCo** multiple robots partition the environment into different regions in an adaptive way and each robot takes responsibility for covering one of these regions. Moreover, the robots communicate indirectly via depositing/detecting pheromones in the environment. Characteristic of **A-StiCo** is that the movement policy for the individual robots is intentionally kept very simple, so that it can be implemented on any unicycle vehicle with minimum computation capability. Crucial for the practical value of any coverage approach is its robustness. Simulation studies are presented which show that **A-StiCo** allows robot teams to fulfill coverage missions in a very efficient and robust way. In particular, the results demonstrate that this approach achieves very robust coverage behavior at the team level under different challenging circumstances (including robot failures and non-convex environments).

1 Introduction

In recent years there has been a rapidly growing interest in using teams of mobile robots for covering and patrolling environments of different types and complexities. This interest is mainly motivated by the broad spectrum of potential civilian, industrial and military applications of multi-robot surveillance systems. Examples of such applications are the protection of safety-critical technical infrastructures, the safeguarding of country borders, and the monitoring of high-risk regions and danger zones which cannot be entered by humans in the case of a nuclear incident, a bio-hazard or a military conflict. Triggered by this interest, today automated coverage is a well established topic in multi-robot research which is considered to be of particular practical relevance.

Wagner et al. [19] were the first who suggested to use stigmergic multi-robot coordination for covering/patrolling the environment. They used robots which had the ability to deposit/detect pheromones for modeling an un-mapped environment as a graph, and they proposed to use basic graph search algorithms (such as Depth-First-Search and Breadth-First-Search) for solving robotic coverage problems. Many other researchers used this graph-based modeling scheme in order to design solutions for multi-robot patrolling/covering problems [8, 9, 11, 12, 20]. For example, in [8] Elor and Bruckstein mixed *cycle finding* algorithm with *spreading* algorithm in order to provide a finite-time cycle-based patrolling approach. In contrast to these graph-based techniques, Voronoi-based techniques have recently been introduced for solving robot coverage problems (e.g., see Cortes et al. [3, 4] and Schwager et al. [17, 18]). Based on this idea many researchers have proposed modified covering approaches which are adaptable to changes in the environment and are provably convergent (e.g., [1, 17]). However, the currently available theoretical and algorithmic approaches to multi-robot coverage typically require a group of robots which are capable of direct communication. Additionally, in most cases they also need very complex mathematical computations (e.g., calculating margins and center of mass for an individual Voronoi-region) which also limits their potential real-world usage. Moreover, many of these methods are based on unrealistic assumptions. Examples of such assumptions are idealized sensors/actuators or sensors with infinite range (e.g. [16]), convexity and/or stationarity of the environment (e.g. [17]), the availability of unlimited communication bandwidth, and fully reliable direct communication links (e.g. [4]).

Recently we proposed a novel stigmergy-based coverage approach called **StiCo** [15] which avoids this type of assumptions. This approach is of a very low computational complexity and is designed for robots with very simple low-range sensors. Moreover, this approach does not rely on direct communication among robots. Instead, the covering robots coordinate on the basis of an indirect communication principle known as stigmergy. In this paper we describe an extended version of **StiCo** called **A-StiCo** ("Adaptive Stigmergic Coverage"). As its name indicates, **A-StiCo** aims at enabling robots to respond *adaptively* to dynamical changes in the environment.

The rest of this article is organized as follows. Section 2 introduces some preliminaries related to the research described here. **A-StiCo** is described in detail in Section 3. Simulation results are shown in Section 4 and Section 5 concludes the article.

2 Preliminaries

This section provides some background information on different classes of coverage behavior and on the biological motivation underlying **A-StiCo**. References to relevant related work are given in Section 1.

2.1 Coverage Behaviors

In general, a *surveillance* application is characterized by a unique set of requirements. Exploration and Coverage are two fundamental research issues in these applications. Research on exploration and coverage determines how well an area is explored and monitored, respectively. In order to explore the environment, robots decide how to move based on their current information for gaining the most possible new information about the environment. Instead, coverage algorithms determine the spatial relationship of robots in order to optimize some performance functions. In general coverage approaches are classified in three classes [10]: (1) *Blanket coverage*, in which the objective is to achieve a static arrangement of elements that maximizes the detection rate of targets appearing within the coverage area. (2) *Barrier coverage*, in which the objective is to achieve a static arrangement of elements that minimizes the probability of undetected enemy penetration through the barrier. (3) *Sweep coverage*, in which the objective is to move a group of elements across a coverage area in a manner which addresses a specified balance between maximizing the number of detections per time and minimizing the number of missed detections per area. In this paper, the main goal is to achieve a *Blanket coverage* which maximizes the detection rate of the robots. Therefore, robots partition the environment into circular regions, and each robot guards one region by circling around it.

2.2 Biological Inspiration

Stigmergy is an indirect form of communication which applies modifications to environment for exchanging information among agents of same species. One of the key features of this kind of communication is its local characteristics where just the immediate neighbors access to the information. Examples of stigmergy can be observed in many kinds of mammals (e.g. rodents, ungulates, carnivores, and prosimians), and many kinds of social insects (e.g. termites, bees, and ants). In particular, many new approaches for problem solving take inspiration from Ant Colonies. Ants use a set of chemicals produced by their living organism (i.e. natural pheromones) that transmit a message to other members of the same species and assists in finding food, locating mate, avoiding danger and help coordinate their social activities.

In computer science, and especially in the field of ant algorithms (e.g., [5]), a number of computational variants of stigmergy have been developed and it has been shown that they allow for very efficient distributed control and optimization in a variety of problem domains (e.g., [6]). In addition to efficiency and distributedness, stigmergy-based coordination has several other properties which are also essential to multi-robot covering algorithms, including robustness, scalability, adaptivity and simplicity.

3 Design of the A-StiCo Approach

3.1 Problem Formulation

The basic intention behind the work described here is to design a *motion policy* which enables a group of *robots*, each equipped only with simple *sensors*, to efficiently *cover* a possibly complex *environment*. Moreover, the basic idea pursued is to utilize the principle of pheromone-based coordination and to let each robot deposit *pheromones* on boundaries of its *territory* to inform the others about the already covered areas.

We assume the environment as an *allowable environment* with area A, where "allowable environment" is defined as a closed and simply connected set which has a finite number of strict concavities [2]. Each robot is a *Dubins* vehicle [7] described by the dynamical system

$$\dot{x} = v\cos\theta, \quad \dot{y} = v\sin\theta, \quad \dot{\theta} = \omega, \tag{1}$$

where $x, y \in \mathbb{R}$ denote the vehicle position and $\theta \in \mathbb{S}^1$ denotes its orientation. The control inputs v and ω, describe the forward linear velocity and the angular velocity of the vehicle respectively, while v is set equal to v_0 (i.e. the nonholonomic vehicle is constrained to move at a constant linear speed) and the control input ω takes value in $[-1/\rho, 1/\rho]$; $1/\rho$ being the maximum curvature.

Each robot is equipped with two ant-antenna like sensors, placed on the front-right and front-left corners. These sensors have the ability to detect presence of pheromones from a predetermined distance called R_d, where R_d is considered to be very small. By pheromone, we consider an electrical marker placed at an arbitrary position (x_p, y_p). The pheromone is fully evaporated after time T_e. Inspired by real ants, each robot considers a circular environment of area A_T as its territory and circles around this area persistently. The area of territory is related to angular and linear velocity of robot as: $A_T = \pi(v/\omega)^2$. The motion policy tells a robot what to do at each iteration of time. Therefore, when a robot detects pheromone, it decides based on this policy what to do next. We consider an environment to be covered, as a condition that no two robot territories share a common area of the environment. Therefore, the motion policy should guide the robots in a way that their territory intersections decrease as time passes. When the full coverage is achieved (i.e. no territories have intersection), each robot patrols its territory by moving on the territory border, persistently.

In Fig. 1 a group of robots, moving in an allowable environment are illustrated.

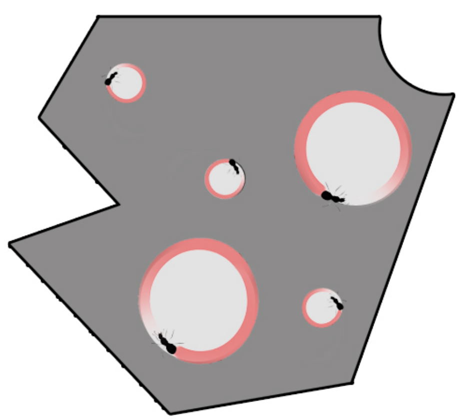


Figure 1: An allowable environment shown in dark gray. Black ants represent the robots, red circle boundaries are the pheromones, and territory of each robot is shown with light gray.

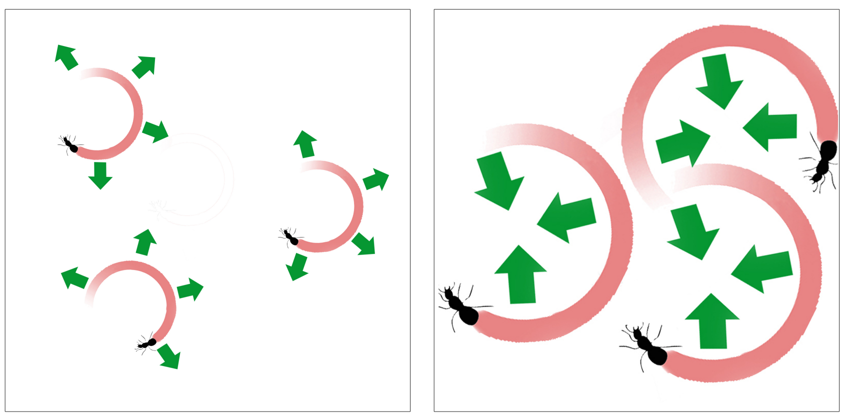
3.2 Basic Motion Policy in StiCo

A-StiCo adopts the basic motion policy of our **StiCo** approach [15]. In short, **StiCo** principle is as following: Each robot starts to move with a constant forward linear velocity, and a constant angular velocity, which results in a circular motion on the border of a territory. The forward linear velocity remains constant during the whole mission. However, in different situations the angular velocity might increase or decrease based on the motion policy. Consider one sensor as the interior sensor (the one nearer to the center of territory) and the other one as the exterior sensor. When the interior sensor detects a pheromone, it indicates to the robot that it is about entering another territory, and therefore the robot changes its circling direction immediately. In this way, the robot establishes its territory in a new region without any intersection with the other territory.

3.3 Adaptive Motion Policy in A-StiCo

The **StiCo** coverage approach described in previous subsection works good in various environments. However, when we use a fixed number of robots with fixed territory radius for environments of different sizes, the larger the environment is the less efficient the approach covers the environment. Therefore, to improve the scalability and robustness of this approach, we add an adaptive behavior to the **StiCo** in which robots adjust their angular velocity (and as a consequence their territory area), for efficient coverage of the environment.

Therefore, each robot calculates the time that it has not detected any pheromone. As soon as the time passes a predefined threshold, the robot increases its territory by decreasing the angular velocity (i.e. $\omega_{new} = \omega_{old} - \Delta\omega$). This behavior is illustrated in Fig. 2a. Reversely, when each robot detects pheromones frequently, it decreases its territory area by increasing the angular velocity (i.e. $\omega_{new} = \omega_{old} + \Delta\omega$) as shown in Fig. 2b. Therefore, robots tend to increase their territory area as long as no intersection with other territories happens.



(a) (b)

Figure 2: **A-StiCo** adaptation law: (a) when a robot do not detect other robots in nearby, expands its territory area. (b) when a robot detects other robots in nearby, shrink its territory area.

This **A-StiCo** coverage approach is detailed in Algorithm 1 (ϵ is the adaptation coefficient used for adjusting the speed of territories expansion).

4 Simulation Results

In this section, we demonstrate the evolution of **A-StiCo** on three simulation scenarios. In the first scenario, robots are initialized in the center of an obstacle-free environment and disperse in it homogeneously in order to partition the environment into circular regions. In this simulation, the scalability of **A-StiCo** is demonstrated by using a unique motion policy for robotic swarms of different sizes. In the second scenario, the robust behavior of **A-StiCo** in response to robot failures is illustrated. Finally, in the third simulation, obstacles are used to generate a non-convex coverage problem. The main goal of this scenario is to demonstrate the robustness of **A-StiCo** in complex environments.

All of the simulations are implemented on a robotic swarm of identical members initialized in the center of a $40m \times 40m$ field. The pheromones are simulated with a high resolution, equal to 300×300 and the evaporation time is $T_e = 1.5s$. Moreover, we pay careful attention to numerical accuracy and optimization issues in the pheromones update policy.

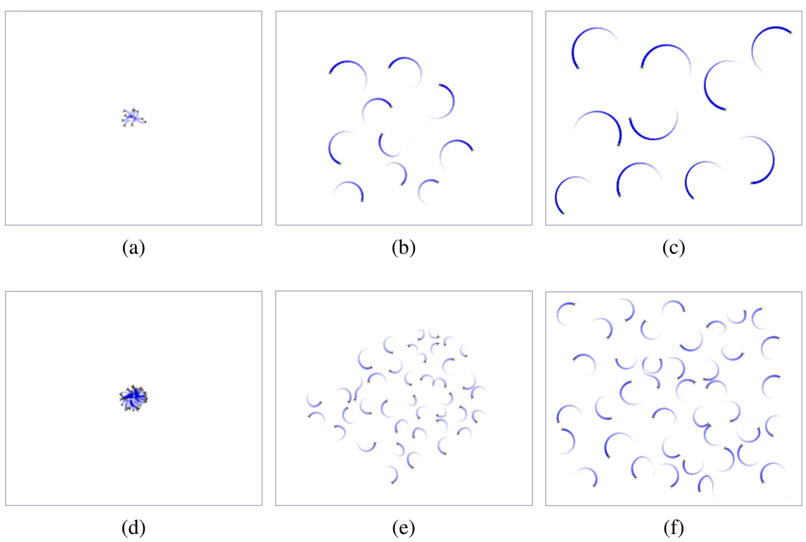
4.1 A-StiCo in a Convex Environment

In this simulation we show that by adding adaptive behavior to the **StiCo** approach, efficient coverage results are achieved. In **A-StiCo**, when a robot does not detect pheromone for a while, it decreases its angular speed

Algorithm 1 A-StiCo: Adaptive Stigmergic Coverage Approach for an individual robot

```
Require: robot can leave and detect pheromone trails
Initialize: Choose circling direction (CW/CCW)
Initialize: Set angular velocity to ω0
loop
    while (no pheromone is detected) do
        Circle around
        ω := ω − ϵ.Δω
    end while
    ω := ω + Δω
    if (interior sensor detects pheromone) then
        Reverse the circling direction
    else
        while (pheromone is detected) do
            Rotate
        end while
    end if
end loop
```

(w_0). Consequently, the territory area is expanded and the robot guards a larger region. Otherwise, when a robot detects pheromone very often (which means that many robots are moving nearby), it increases its angular velocity. Consequently, the territory area becomes smaller and the robot guards a smaller region. Therefore, Robots are able to change their territory area and cover the environment more effectively. Fig. 3 depicts the evolution of **A-StiCo** for two swarms of 10 and 40 robots. In both simulations, robots start from the same initial conditions.



(a) (b) (c) (d) (e) (f)

Figure 3: The evolution of **A-StiCo**: (a)-(c) Initial, intermediate, and final snapshots after $250s$, for 10 robots. (d)-(f) Initial, intermediate, and final snapshots after $250s$, for 40 robots.

4.2 Robustness of A-StiCo to Robot Failures

One of the key features of a distributed approach is robustness to individual failures. Therefore, in this scenario we illustrate the efficient behavior of **A-StiCo** in response to a 57% failure of the swarm. Consider a group of 40 robots which are homogeneously positioned in the environment (Fig. 4a). We assume 23 robots are failing to work and eliminate them from this configuration. Due to this large failure in the network, a drastic inhomogeneity is seen which produces vast uncovered regions (Fig. 4b). However, based on adaptive behavior of robots in **A-StiCo** approach, each robot adjusts its territorial area based on the uncovered areas in its vicinity and it will share the area of its territory with its neighbors. Therefore, soon the network obtain an efficient configuration as shown in Fig. 4c.

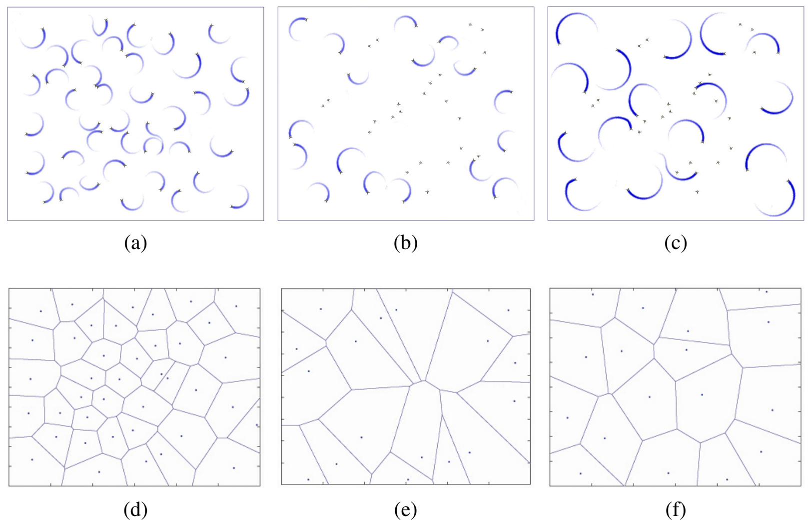


Figure 4: The robustness examination of **A-StiCo** coverage algorithm: (a) Homogeneous coverage after $250s$, (b) Failure of 23 robots at T=$250s$, (c) Final position after $350s$ (d)-(f) Voronoi diagrams of territories centers, each corresponding to upside snapshot.

In order to explore the robust behavior of **A-StiCo** in more detail, we implemented this approach on the same group of robots with different failure percentages (starting form failure of one robot which is 2.5%, up to 39 robot failures which is 97.5%. We defined the recovery time as the time that robots need to adopt their positioning configuration for covering the most possible area of the environment after failures. This recovery time is measured for each simulation, and the results are illustrated in Fig. 5.

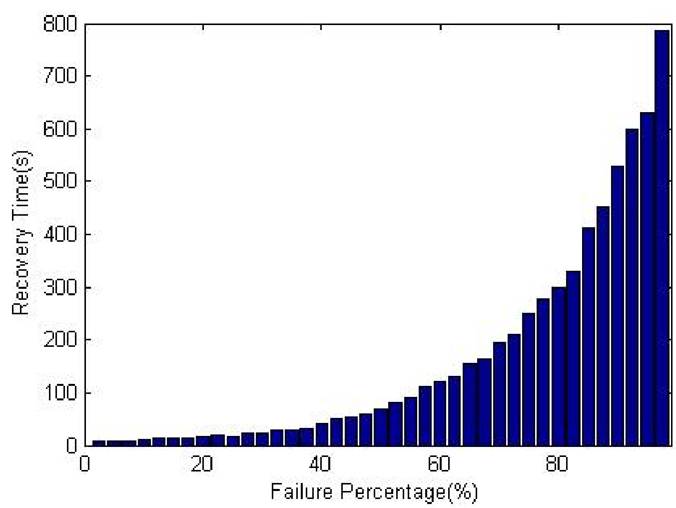


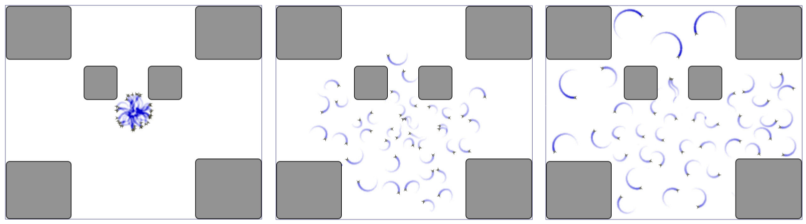
Figure 5: Recovery time for different failure percentages

From the results of Fig. 5, it can be seen that the robotic swarm is very robust to failures up to 60%. However, for larger failures, it takes relatively long time for the robots to adopt their configuration to the new conditions.

4.3 Robustness of A-StiCo to Environmental non-Convexities

In this simulation scenario, we consider a non-convex environment as shown in Fig. 6a. This environment can represent a devastated area after an earthquake, or a street map in an emergency condition.

For coverage of this environment, a group of 40 robots are initiated at the center of the environment with different initial angles. **A-StiCo** is executed on this group and snapshots of this simulation are illustrated in Figs 6a-6c. (In this simulation, artificial pheromones are deposited on the borders of obstacles to make them detectable for robots).



(a) (b) (c)

Figure 6: Evolution of **StiCo** in a non-convex environment: (a) Initial snapshot. (b) Intermediate snapshot. (c) Final snapshot.

As shown in the Figs 6a-6c, the **A-StiCo** approach is robust to environmental complexities. Although, robots are not equipped with any path planning system, independent of where the obstacles are placed, robots can easily disperse in the environment homogeneously.

5 Conclusion

This article described an extension of the **StiCo** multi-robot coverage approach [15]. **A-StiCo** is a fully distributed motion policy which allows for a very effective and efficient coverage performance. Compared to existing coverage approaches, **A-StiCo** shows several important advantages, including scalability, very low computational complexity and memory requirements, and easy functional extensibility. This makes **A-StiCo** distinct from all other currently available multi-robot coverage approaches. The robust behavior of **A-StiCo** was explored, and simulation results showed that even in the case of robot failures, or environmental complexities, the algorithm performs well.

We think the simulation results justify to invest further research in **StiCo/A-StiCo**. Currently we are working on an implementation of **A-StiCo** on a group of e-puck robots in our SwarmLab (http://swarmlab.unimaas.nl/). Based on this experimental test-bed it will be possible to explore the efficiency and robustness of this coverage approach in real-world settings. We also see interesting options for extending **A-StiCo**, and we currently look into the usage of a more advanced pheromone concept. **A-StiCo**, in its current form, does not require that pheromones have the ability of data storage. This makes sense because chemical pheromones (as used by animals) are not appropriate for storing information. However, digital pheromones, (e.g. RFIDs) recently studied in various papers (e.g., [13,14,21]) can be used for storing large amount of data in the markers easily.

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