A Bioinspired Coordination Strategy for Controlling of Multiple Robots in Surveillance Tasks

Rodrigo Calvo, Janderson R. de Oliveira, and Roseli A. F. Romero
Department of Computer Sciences
University of Sao Paulo
Sao Carlos - SP, Brazil
Email: {rcalvo,jrodrigo,rafrance}@icmc.usp.br

Mauricio Figueiredo
Department of Computer Sciences
Federal University of Sao Carlos
Sao Carlos - SP, Brazil
Email: mauricio@dc.ufscar.br

***Abstract*—There are tasks that the multiple agent system approach is very appropriate for improving performance. Among them are: environment exploration, mineral mining, mine sweeping, surveillance, and rescue operations. The expected advantage is not a mere consequence of putting together many agents. An efficient coordination strategy is decisive to reach performance improvements. In the present paper, a new strategy is proposed for coordination of multiple robot systems applied to exploration and surveillance tasks. The coordination strategy is distributed and on-line. It is inspired in biological mechanisms that define the social organization of swarm systems; specifically, it is based on a modified version of usual artificial ant systems. Two versions of the proposal are evaluated. The experiments consider two performance criteria: the average of the numbers of surveillance epochs and average of the surveillance time intervals. Simulation results confirm that exploration and surveillance emerge from a synergy of individual robot behaviors. Data analyses show the coordination strategy is effective and suitable to execute exploration and surveillance tasks.**

Keywords-multiple robot system; surveillance task; coordination strategy; ant colony system; swarm systems.

I. Introduction

A multiple agent system is well characterized if its dynamics reflect some synergy, that is, global behaviors emerge from the individual ones improving capabilities and performance to reach a specific goal. If only one agent of a group achieves equally the same goal with the same performance the entire group does, then at first,the group of agents are not a multiple agent system. Regarding as multiple robots system, this present paper is an extension of approach proposed in [1], where a robots team is able to monitor an environment independently of adopted configuration. In the other words, the way by which walls (or obstacles) are placed in an environment does not limit the accomplishment of exploration and surveillance tasks.

There are many applications to which multiple agent systems are the suitable approach to be adopted, such as: rescue operations in catastrophic events; fire extinction; and exploration in hostile environment [2][3][4]. Some of the main reasons that justify this choice, among others, are: great dimension of the task and reduced resources (e.g., velocity, strength, energy) provided for a single agent; necessity to adaptation to spatial or temporal variation of service demands and robustness. For some tasks this approach is mandatory; for others it is a matter of convenience to increase the quality, to improve the performance or to save monetary funds.

Nowadays, the technology reaches more sophisticated levels providing environment support and embedded supplies. These improvements bring closer the possibility of multiple agent systems to become usual. The strong expectation associated to this possibility captivates the attention of the scientific community. Different aspects are investigated in multiple agent systems, such as: agent communication and information merging [5][6][7][8]. Another important aspect is the agent coordination that allows the system accomplishes efficiently general tasks such as: exploration, coverage, surveillance, among others.

On the one hand, coordination strategies are designed to provide multiple agent systems with a set of characteristics, e.g., decentralized coordination, small redundancy of agent efforts and strong cooperative behavior. On the other hand, designers devote effort to propose coordination strategies that are dependent on the least number of parameters as possible. A tricky parameter is the number of agents. Another requirement that may depreciate the strategy is the need to have total knowledge of the environment.

According to a technique described in [9] robots construct a common map cooperatively. It is introduced the notion of a frontier, which is a boundary between the explored and unexplored areas. As robots move, new boundaries are detected and frontiers are grouped in regions. Then, the robots navigate toward the centroid of the closest region, while sharing maps. The strategy is a centralized type since A^* algorithm considers all information that the robots provide and the algorithm output defines the next steering direction of each robot. The strategy does not avoid unnecessary redundancy of robot efforts.

The problem of surveillance using multiple agents is investigated as a problem of a cooperative patrolling in [10]. A mathematical formulation is proposed as a minimization problem. The objective to minimize the refresh time, that is, the time necessary for the agents patrol completely the environment. The solution they find is an approximation algorithm of polynomial computational cost based on a topological graph representation and a path-covering procedure. The strategy depends totally on the knowledge of the environment.

Methods based on stimergy fields for cooperation have been recently employed in the context of robotic exploration [11][12][13]. They rely on a mechanism of indirect communication among the agents which allows their actions to be influenced by a trace left previously in the environment by the robot. In this way, a task can be accomplished in an efficient manner. A different coordination scheme in [14] is proposed based on potential fields in which repulsive forces repel robots from each other and obstacles. Starting navigation from the same region, the robots keep moving until repulsive forces cancel each other. At this moment the sensor network is settled and robots stop. This approach ensures the coverage task if the number of robots is sufficiently great. Unfortunately, the authors do not show how to find the minimum number of robots. Therefore there always exists a possibility that the strategy fails.

Coverage tasks are the focus of the investigation in [15]. The distributed coordination strategy, based on the Voronoi diagram and Delaunay triangulation, is proposed to maximize the connected coverage area. The strategy is robust to robot failures. Voronoi diagram is also adopted to solve the connected coverage problem in [16]. Despite these strategies solve a connected coverage problem, both do not sense completely the environment, that is, not all parts of the environment are visited by any robot.

The problem of coordination of multiple agents is considered complex [17][6]. Coordination strategies based solely on mathematical formulation and on agent and environment models are very parameter dependent and suffer critical degradation due to agent failure [18][15][16]. Furthermore, the problem of coordination of multiple robots that execute a surveillance task is proved to be NP-hard [10]. Bio-inspired theories provide fundamentals to design alternative strategies that overcome the main difficulties that become traditional strategies vain [19][20].

Particularly, the artificial analog versions of biological mechanisms that define the social organization dynamics, observed in some swarm systems, are very appropriate in applications involving multiple agents, for example, decentralized control, communication and coordination [21][22][23].

In our previous works, some initial ideas about construction of a new bioinspired based model for a control strategy of multiple robots were proposed in [24]. It is named *Inverse Ant System-Based Surveillance System* (IAS-SS). In a preliminary model of IAS-SS, it was considered distinct steering direction mechanisms and the feature of robustness in regarding the number of robots adopted. As an extension, in [1] was shown that the system does not depend on knowledge of the environment, where the agents act in environments with different configurations (arrangement of obstacles). In order to prove the efficiency of communication way among the agents rather than that adopted by biological agents, a parametric analysis was performed in [25], using various stigmergy mechanisms.

In the present work, an enhancement of IAS-SS strategy is proposed through a more complete description. It is designed according to a modified version of the ant system algorithm presented in [26]. In this strategy, the agents were able to indirect communication as the biological agents are, but their reaction to the pheromone is distinct, steering directions are defined to guide preferably the robot to where there is low quantity of pheromone. IAS-SS strategy is primarily for the coordination of multiple robots applied to surveillance and exploration tasks. Some characteristics of IAS-SS are: decentralized, on-line, and parameter independent from both the number of robots and the environment structure. Two versions of the strategy IAS-SS are compared with a total random strategy. Different experiments are considered, each of which varying a specific parameter: number of robots, the environment scale, and initial position. Results show that exploration and surveillance tasks are effectively executed and the respective general behaviors emerge from the individual robot behavior (move to where there is less pheromone).

Since the task of modeling all possible events, accurately, in real world through mathematical models is not trivial, the main contribution of this paper is a simple coordination strategy based on a modified version of the traditional ant system, that is, the robots are attracted to the region of the environment with low amount of pheromone. The behavior of explorationt and surveillance are generated only by the information supplied by the deposited pheromone with few parameters to be adjusted. It is necessary neither robot's position nor their local map environment. It is worth to be emphasized the way in which the robots deposit pheromone. This substance is left in the frontal area of robots, instead of the positions occupied that generate a pheromone trail. These characteristics are not found in other approaches existing in the literature.

This paper is organized such as it follows. In Section II is presented the basic concepts of the artificial ant system theory. In Section III, the mathematical formulation of the surveillance problem is presented. The multiple robot system and the coordination strategy IAS-SS are focused in Section IV. The pheromone evaporation dynamics, the mechanisms of pheromone releasing, and the procedure to determine the robot steering direction are also defined. In Section V simulation results are reported. The main contributions and relevant aspects of this paper as well as expectations for future works are highlighted in Section VI.

II. Ant System

Surprisingly, the complex tasks that ant colonies perform, such as object transportation and build edges, demand relatively more capabilities that a single ant is endowed [27][28].

Biological ants have two known mechanisms to establish communication, namely, direct and indirect. Biological ants not only exchange stimuli when they meet; but also exchange stimuli indirectly (a communication mechanism called stimergy). Ants deposit a specific type of substance (pheromone) on the ground while they move. There are different types of pheromone, each of which associated with a particular meaning. If a pheromone trail is found and this pheromone type indicates food, then more and more ants follow this trail, depositing more pheromone and reinforcing the stimuli. An opposite behavior happens if the pheromone is of the aversive type, indicating risk and danger. Stimergy mechanism is considered as one of the factors that decisively contribute to amplify the capabilities of a single ant. Ant colonies use the stimergy mechanism to coordinate their activities in a distributed way [29].

Artificial ant systems are the artificial counterparts of the biological ant colonies, designed to solve complex problems, among others: optimization combinatorial problems [26]. Analogously artificial ants (e.g., robots) are able to use the stimergic communication. Pheromone trail provides a type of distributed information that artificial agents may use to take decisions or modify to express previous experiences [30]. A distributed coordination behavior emerges from this capability, providing solutions to problems associated with exploration in hyper-spaces.

III. Definitions and Preliminary Concepts

There are different mathematical formulation in the literature. For example, in [10] the concept of *viewpoint* is defined. *Viewpoints* are specific points in the environment such that from those points it is possible to sense the whole environment. Then the robots have to go to them repeatedly in order to keep the environment sensed completely. The optimal surveillance task is defined as the minimization of the largest interval between two consecutive instants that any robot reaches a particular *viewpoint*, considering all *viewpoints* and during all time the task lasts.

Informally, the surveillance task means the task of keeping endlessly a target under closed observation. In this paper, the target is an environment. It is not necessary to keep all points of the environment under observation at the same time, but every point has to be observed repeatedly while the task lasts. If a set of agents are considered to carry out the task, the agents have to follow trajectories that allow them to sense all parts of the environment again and again. Clearly, it is not necessary that each agent goes to every point, but every point has to be observed by at least one agent (anyone) repeatedly. Then, the execution of the surveillance task is considered effective if the environment is completely and continually sensed. Moreover, the smaller is the maximum interval between two consecutive sensing, considering any particular point of the environment, the more efficient is the execution of the surveillance task.

Two terms used in this work help the readers to understand how the surveillance task is evaluated in this work: *Surveillance Epoch (SE)* and *Surveillance Interval (SI)*. A surveillance interval is any interval of time in which all points of the environment are sensed at least once; and at least one point is sensed exactly once. This interval corresponds to a portion of the surveillance task and this portion is called surveillance epoch. If the surveillance intervals are considered from the start of the task, the SI's are uniquely determined. Starting from T_0^*, the agents start to move through the environment, sensing the environment. After a time, precisely at time T_1^*, all points are sensed at least once; and at least one point is sensed exactly once. The interval between T_0^* and T_1^* is the first SI. The second SI begins at T_1^*. It is important to notice that at T_1^* no point is considered sensed anymore, that is, a new reckoning starts at T_1^* to indicate the sensed points. The agents keep moving continuously. At T_2^* all points are sensed at least once; and at least one point is sensed exactly once (considering a new reckoning starts for the second SI). The interval between T_1^* and T_2^* is the second SI. All other SI's are defined analogously. The surveillance task is evaluated measuring the maximum length of the intervals SI.

In order to put the meaning of the surveillance task more rigorous the respective mathematical model is built next.

Consider that robots r_k, $k = 1, \ldots, N$ move in a planar space $Q \subset \mathbb{R}^2$ and that an arbitrary point in Q is denoted by q. Assume that the time t is discrete. Let L_t^k, $L_t^k \subset Q$, be the area that the r_k-th robot senses at instant t. Hence, the r_k-th robot senses a point q at instant t, if $q \in L_t^k$. Define a function $I_k(.,.)$ to associate a point q with the respective state considering the r_k-th robot, that is, $q \in L_t^k$ if and only if $I_k(q,t) = 1$. Define also a function $\Omega_i(.,.)$ to associate a point q with the number of times it is sensed from T_{i-1}^* up to t, considering all robots r_k, that is:

$$\Omega_i(q,t) = \begin{cases} 0, \text{if } t = T_{i-1}^* \\ \sum\limits_{\mu=T_{i-1}^*}^{t} \sum\limits_{k=1}^{N} I_k(q,\mu), \text{otherwise} \end{cases} \tag{1}$$

Then, this paper focuses on the minimization problem such as it follows:

$$\min \max_{1 \le i \le C} \left(T_i^* - T_{i-1}^* \right) \tag{2}$$

subject to:

$$\Omega_i(q, T_i^*) \ge 1, \quad \forall q \in Q$$

$$\exists q \in Q | \Omega_i(q, T_i^*) = 1,$$

$$\sum_{i=1}^{C}(T_i^* - T_{i-1}^*) \leq T^F$$

where: T_i^* and T_{i-1}^* are the limits of the $i-th$ surveillance interval; $C \geq 0$ is number of completed SE and T^F denotes the time when the surveillance task ends.

It is important for the reader to notice that the problem defined earlier in equation 2 is not solved here exactly, but only in an approximated way. This is almost a rule since this problem is known to be very complex, when the number of robot is big. This is the case in this paper. Multiple identical mobile robots are considered to carry out the surveillance task. Every robot is equipped with a set of sensor devices that allow the robots observe the environment. According to [10] the surveillance task problem such as described there is a NP-hard problem.

One among the aspects of the surveillance task problem considered in this paper is that the environment is unknown. By focusing on this aspect, it is important to notice that the exploration task may be regard as part of the surveillance task, since the environment is completely explored at the end of the first surveillance epoch. At this time all points of the environment are sensed, that is, there is no point remains to be found. Then, in what follows the focus is on the surveillance task and the exploration task is a mere consequence.

IV. Inverse Ant System-Based Surveillance System (IAS-SS)

The multiple agent system approach is adopted to solve the surveillance task problem such as described in the former section. The agents are multiple identical mobile robots each of which equipped with a sensor for detecting a particular characteristic of the environment.

At first glance, this approach seems attractive, that is, a plausible conclusion is: multiple robots execute more efficiently the surveillance task than a single one. However this conclusion is true if, at least, there is a capable strategy to coordinate suitably the robots. It means that the strategy has to generate trajectories for every robot, leading them repeatedly to all parts of the environment, satisfying some performance criteria, e.g., minimization of the interval between two consecutive instants a point in the environment is sensed, considering all points.

Putting together: performance requirements, solution restrictions, and strategy characteristics; makes the design work a hard task (such as asserted in [10], see comments in the previous section).

The system proposed, called *Inverse Ant System-Based Surveillance System* (IAS-SS), is designed according to the main ideas of the artificial ant system. In short, the IAS-SS system is a multiple robot system. The robot's cybernetic system consists of two components: the navigation controller and the pheromone disperser. The pheromone disperser is one of the components of the robot's cybernetic system, since it is related to the robot's indirect communication system. The Figure 1 represents the components of the cybernetic system and the respective connections with other elements of the system, including the environment.

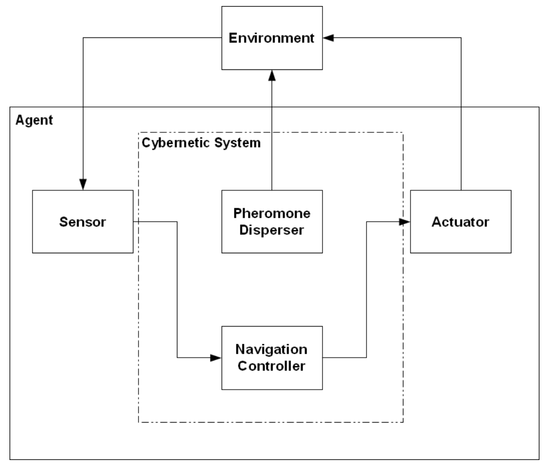


Figure 1. Cybernetic system architectural diagram for a single robot.

The strategy, called *IAS-SS strategy* , is for coordination of the IAS-SS system's robots applied to surveillance tasks. The coordination strategy is a distributed one, that is, every robot moves independently and takes decisions based on the stimuli it receives from the environment. The IAS-SS coordination strategy is a reactive (real-time) strategy, does not generate decision dead-locks, and is computational low-cost.

The IAS-SS coordination strategy is based on the indirect communication mechanism (*stigmergy*) the biological ant colonies exhibit. The IAS-SS coordination strategy generates the following general system dynamics. While the robots navigate they deposit a specific substance into the environment. This substance is called *pheromone*, since it is the analogue of the pheromone in biological ant colonies. At each time the robot sensor detects the stimuli from the environment corresponding to the total amount of the pheromone deposited on the area defined by the sensor range. The amount of pheromone detected is the accumulated pheromone deposited on that area considering all robots. After that the robot adjusts its navigation direction, deposits the pheromone and moves.

The IAS-SS strategy is completely described in the next subsections. Among other elements described, are: the navigation system and the steering direction mechanisms; and pheromone disperser. All other elements of the IAS-SS system will be considered as well. In the end, all of them will be described in detail.

A. Navigation System

According to the IAS-SS coordination strategy, the robot navigation system consists of two subsystems: surveillance system and obstacle avoidance system. Only one is active at each time. Most part of the time the surveillance system is active and the steering direction is determined according to it. The trajectories the surveillance navigation system generates cause the robots execute the surveillance task. The trajectories do not lead robots to collision situations as well, with rare exceptions. In order to avoid completely any possible collision situation, the obstacle avoidance system is active only if the robot is very close to a wall or an other robot.

Although the obstacle avoidance system is not the main concern in this paper, it is briefly described. As long as robots are close to an obstacle, the amount of pheromone in its boundary region is increased. Then, the robots generate the obstacle avoidance behavior due to the high amount of pheromone. Therefore, obstacle avoidance is an emergent behavior of the IAS-SS strategy. The trajectories generated by the strategy does not guide the robots to a collision situation. Besides the exploration and surveillance tasks, the robots are able to avoid obstacles, keeping a reasonable distance from them.

However, there are some exceptions when a robot collides against another robot or against an obstacle according to its physical characteristics. In this sense, it is used a mechanism for obstacle avoidance based on fuzzy logic [31] that adjusts the steering direction of the robot using the information about its distance to an obstacle. The details of the mechanism based on fuzzy logic can be found in [32]. It is enough to say that this mechanism is active only when the distance between the robot and an obstacle is smaller than a predefined constant η.

The general description of steering direction mechanism the surveillance navigation system implements is such as follows. At each time a set of stimuli is detected, corresponding to the amount of the pheromone deposited at different angles and same specific distance (at the range border) in front of the robot. The lesser is the detected amount of the pheromone detected the greater is the probability that the robot takes the navigation direction equal to the angle where this amount of pheromone is.

According to this strategy robots tend to move to the directions where there is low amount of pheromone. The general robot behavior observed is that the robot moves to unexplored areas or areas robots seldom visit.

Considering the IAS-SS coordination, the logic associated with the decision that chooses the steering direction angle is opposite of that adopted in the traditional ant system theory. The logic adopted there generates a positive feedback, that is, the greater is the amount of the pheromone the greater is the probability of the agent to follow the respective direction.

Two versions of the steering angle mechanism are described. The first one, called Stochastic Sampling, considers all possible pheromone stimuli that the sensor detects at the border of its range. The second, called Best Ranked Stochastic Sampling, determines the adjusting of steering angle based on a select set of stimuli detected at the border of the sensor range.

The mathematical models for these two versions of the steering angle mechanism are described as it follows. Before that, consider two assumptions. First, there are N identical mobile robots r_k, $k = 1, \ldots, N$. Second, the model of the sensor adopted is such that it detects pheromone stimuli at the border of its range (Figure 2). The border is a circumference of a circle of radius R, ahead of the robot, from 90 degrees to the left to 90 degrees to the right of the steering direction. The total range of 180 degrees is divided in identical angle intervals each of which measuring α degrees. The middles of the intervals are settled on angles A_s, such that: $(2S + 1)\alpha = 180$ and $A_s = s\alpha$, where $s \in [-S, S]$ and $s \in \mathbb{N}$.

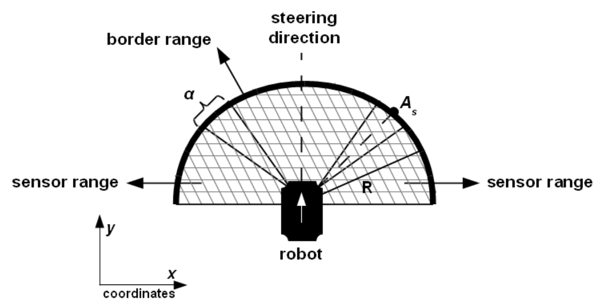


Figure 2. Robot and sensor models

1) Stochastic Sampling Mechanism: A pheromone stimulus corresponds to the amount of pheromone deposited in an angle interval. A probability value assigned to each discrete angle A_s is inversely proportional to the amount of pheromone deposited in the angle interval that is settled on the angle A_s. The lower is the amount of pheromone detected in the angle interval, the higher is the probability associated with the respective angle A_s. Specifically, the probability $P(s)$ assigned to the angle A_s is:

$$P(s) = \frac{1 - \tau_s}{\sum\limits_{i=-S}^{S} (1 - \tau_i)} \tag{3}$$

where τ_s is the amount of pheromone corresponding to the angle interval A_s.

The adjustment of the steering direction is determined according to a discrete random variable a defined through the probability $P(s)$, assuming values in the set $\{A_s \mid s = -S, \ldots, -1, 0, 1, \ldots, S\}$.

At each time t, the adjustment of steering direction is given by:

$$\Theta_k(t) = \Theta_k(t - 1) + \gamma A_s^* \tag{4}$$

where: $\Theta_k(t)$ is the steering angle of the robot k at instant t, $\gamma \in [0, 1]$ is the constant coefficient for smoothing the steering direction adjustment; and $A(s^*)$ is value of the random variable a at instant t for some $s = s^*$.

However, Stochastic Sampling mechanism is not efficient for large areas where the amount of the pheromone deposited is similar on every point. In this case, the amount of pheromone differs a bit and the A_s^* chosen may define bad steering directions due to the stochastic nature of the mechanism. For reducing the possibility of this shortcoming, a second different mechanism is described and investigated below.

2) Best Ranked Stochastic Sampling Mechanism: Differently from the Stochastic Sampling Mechanism, not all angle A_s are considered to define the steering direction, but only two subsets, U and V, such that the respective cardinalities are φ and ω; and $\varphi + \omega \leq (2S+1)$. The subset U consists of angles A_s associated with the least detected amount of pheromone. The subset V consists of elements chosen randomly, according to an uniform distribution, from the angles A_s that are not in the subset U.

The rules for building the subsets U and V are such as follows:

- **Subset** U

  if $A_s \in U$ and $A_z \notin U$, then $\tau_s \leq \tau_z$

- **Subset** V

  if $A_s \in V$, then $A_s \notin U$; and A_s are chosen randomly

where: τ_s is defined according to equation 3 and $s, z = -S, \ldots, -1, 0, 1, \ldots, S$.

A probability value is assigned to each discrete angle in both of the subsets U and V . The probability assigned to the angle As is inversely proportional to the amount of the pheromone deposited in the respective angle interval and it is defined such as:

$$\overline{P}(s) = \frac{1 - \tau_s}{\sum\limits_{i \in \{s | A_s \in (U \cup V)\}} (1 - \tau_i)} \tag{5}$$

Consider $A_s = A^*$, A_s chosen according to a discrete random variable a defined through the probability $\overline{P}(s)$, assuming values in the set $\{A_s \mid A_s \in (U \vee V)\}$. At each time t, the adjustment of steering direction is given by equation 4:

The basic steps of Best Ranked Stochastic Sampling are described in the Algorithm 1 for a single robot.

Algorithm 1 The Best Ranked Stochastic Sampling Algorithm

```
1: Initialize the parameters φ and ω
2: Detect the amount of the pheromone in the border of
   the sensor range
3: Build the subsets U and V
4: for every angle interval A_s ∈ (U ∪ V) do
5:    Assign to A_s the probability P(s) according to equa-
      tion 5
6: end for
7: Define the next steering direction of the robot according
   to equation 4
8: Back to step 2
```

B. Pheromone Releasing and Evaporation

In traditional artificial ant systems, agents release pheromone on the ground only on their respective positions signaling exactly the robot way [26]. Differently, in this article, the artificial agents in IAS-SS spread out pheromone on a wide area in front of their respective positions, corresponding to the sensor range area.

After the agent determines the steering direction (see equation 4), but before it moves to, it spreads pheromone. The amount of the pheromone deposited on the ground decreases as the distance from the robot increases. Consider that L_t^k is the sensor range area of the kth robot at the iteration t and Q is the entire environment space, respectively, such that $L_t^k \subset Q \subset \mathbb{R}^2$. Then, the amount of the pheromone $\Delta_q^k(t)$ the kth robot deposits at the position q at iteration t is given by:

$$\Delta_q^k(t) = (\tau_{max} - \tau_q(t-1))\Gamma_q^k(t), \text{ and} \tag{6}$$

$$\Gamma_q^k(t) = \begin{cases} \delta\ e^{\frac{-(q-q_k)^2}{\sigma^2}}, \text{if } q \in L_t^k \\ 0, \text{otherwise} \end{cases} \tag{7}$$

where: q_k is the position of the kth robot; τ_{max} is the maximum amount of pheromone; σ is the dispersion; and $\delta \in (0, 1)$.

Multiple robots deposit pheromone in the environment at same time, then the total amount of pheromone deposited on the position q at iteration t depends on the contribution of every robot.

Furthermore, pheromone is not a stable substance, that is, it evaporates according to a specific rate. The total amount of the pheromone that evaporates $\Phi_q(t)$ at position q and time t is modeled according to:

$$\Phi_q(t) = \rho \tau_q(t) \tag{8}$$

where: ρ is the evaporation rate; and $\tau_q(t)$ is the total amount of the pheromone on the position q at iteration t.

Therefore, the total amount of the pheromone $\tau_q(t)$ at q and at time t is given by:

$$\tau_q(t) = (\tau_q(t-1) - \Phi_q(t-1)) + \sum_{k=1}^{N} \Delta_q^k(t) \tag{9}$$

V. Experimental Results

Experiment simulations are developed to evaluate preliminarily the bioinspired coordination strategy IAS-SS based on ant colony algorithm, whereas pheromone causes repulsive behavior of ants instead of attractive for surveillance task. The expectation for surveillance task consists of keeping robots moving among regions of the environment in order to patrol wholly it constantly. The strategy is considered to generate the dynamics of the multiple robot system applied to exploration and surveillance tasks.

The Player/Stage platform (http://robotics.usc.edu/player) is used to perform the experiments. The Player/Stage is a robot server designed by the University of Southern California for distributed control (www.usc.edu). Player operates in a client/server environment and the communication between them occurs through TCP/IP protocol. Stage is a simulator for robots and sensors for two-dimensional environments. Player/Stage models various robots and sensors simulating simultaneously their exact dynamics, including odometric error models. For the purpose of the experiments, the robot Pioneer 2DX is chosen to be modeled in the Player/Stage platform. This robot is equipped with a laser range-finder able to scan the environment (general obstacles, e.g., walls and objects).

The experiments are arranged in four groups. The first consists of experiments focusing on the steering direction mechanisms described in Section IV-A. The mechanisms are compared with a completely uniform one. The second group of experiments is designed to investigate the influence of the configuration of robot initial positions in the task performances. The experiments in the third group concerns specifically the robustness of the coordination strategy regarding to the environment structure. Finally, an analysis the impact of the number of robots on the system performance is presented in of fourth group.

Since the surveillance task requires the robots are in constant moving, the IAS-SS system have to experiment distinct challenges in face of different situations to develop navigation strategies. In order to maximize the watched area at the same instant, the goal of IAS-SS system is to keep robots in different regions avoiding the waste of sensor resource and reducing the time which an area is non-monitored. System efficiency is measured by how short is the time in which a region is non-monitored without sharing regions among robots.

The experimental data are selected and compiled assuming the following meaning. First, the exploration task is executed if the environment is completely covered, that is, the system is capable to provide information to map the environment completely. Moreover, the faster the system completes the task, the better is its performance. Second, the system carries out the surveillance task if there is no instant T* such that after this instant exists a region that is not sensed anymore. Despite this definition for surveillance task is accurate, it is not suitable since may be impossible to find T*. Therefore, for practical purposes, it is important that the system concludes the task continually, that is, the system has to be able to sense the entire environment considering that a new sensing task is started when the system concludes the previous one. Furthermore, the lesser is the maximum time between two consecutive sensing tasks, the better is its performance.

The approach proposed to multi-robot coordination assumes that the environment is represented by occupancy-grid [33]. It uses a reticulated and probabilistic representation of information for modeling the unknown environment according to its laser range-finder readings. It is defined as a multidimensional random field that contains stochastic estimate of the cell states (occupied, not occupied or unknown) in the reticulated space. Each robot builds its own map as it moves and local maps are centralized resulting in a map of explored environment during surveillance task. Mapping module is independent of IAS-SS system. However, it is integrated to verify the explored area while the monitoring occurs. For releasing pheromone, IAS-SS strategy uses the same map generated and allocates in each cell reached by distance sensor a value that corresponds to amount of pheromone in this local.

The environments where IAS-SS system carries out tasks are divided in connected small regions called here rooms. In the context of this following experiments, a room is said to be visited if its central point is reached by any robot. In this case, the group of all central points corresponds to the set $Q \in \mathbb{R}^2$. Hence, the scenario considered here is an instance of the problem formulated in Section III. The system parameters adopted in the experiments are:

- Pheromone releasing and evaporation dynamics:
  - $\sigma = 0.43R$ (radius of the semicircle where the pheromone is deposited, see Figure 2);
  - $\rho = 0.01$ (evaporation rate); and
  - $\tau_q(0) = 0.5$ (the amount of pheromone at iteration $t = 0$).
- Robots and sensors:
  - $R = 8.00$ meters (radius of the semicircle where the pheromone is deposited, see Figure 2);
  - $\gamma = 0.5$ (constant coefficient for smoothing of steering direction adjusting); and
  - Robot speed: 0.5 meter per second.
- Steering direction mechanisms:
  - $S = 360$ (number of angle intervals).
- Simulation parameter:
  - $\eta = 0.3$ meter (maximum distance between the robot and an obstacle to trigger the obstacle avoidance system);
  - Time is discretized by simulation iterations: $t_s \in \mathbb{N}$;

– Maximum number of iterations = 1000.

These parameter values correspond to those that the multiple robot system reaches the best performance, considering all previous experiments executed. Due to aleatory characteristic of mechanisms for adjustment of steering direction, all experiments are executed 10 times (trials). Thus, average of performances are computed to evaluate them. The discrete time is adopted in simulation and it is equivalent to the number of iterations.

In the case of implementation of coordination strategy, all robots are in the same coordinates system. There is a global map of environment, modeled as occupancy grid, where each cell hosts a value that represents its state and the amount of pheromone in this respective local, indicating the time this cell was not monitored. Initially, all cells are setup as unknown with amount of pheromone as 0.5 ($\tau_q(0)$). Since cells provides similar amount of pheromone, the decision make of robots tends to random characteristic. There, it takes some time to robots spread out. As long a robot moves, it builds its own local map in order to transfer it to the global map. Thus, a robot is able to detect pheromone left by other one, because all information about pheromone is avaliable in global map. The position of robot is not relevant in this coordination strategy. The substance deposited by robots is enough to keep them far from each other.

During navigation, robots detect pheromone only in the cells that coincide to border of pheromone sensor. One of cells is elected through probability of equation 3 or 5 for SS and BRSS mechanisms, respectively. Then, the adjustment of steering direction towards the elected cell occurs by 4. Before moving, robots release pheromone (i.e., assign values to cells of occupancy grid) on all cells covered by range of distance sensor, according to equation 9.

A. *Uniform versus Stochastic versus Best Ranked Stochastic Sampling*

Both steering direction strategies, Stochastic Sampling (SS) and Best Ranked Stochastic Sampling (BRSS), have profound random characteristics, since the steering direction adjustment is determined according to a discrete random variable. In order to show that the respective performances are not a mere consequence of a random behavior, the strategies are compared with a uniform strategy (US). This strategy is able to execute neither the exploration nor the surveillance tasks. Different compiled data sets are considered to assess the strategies, namely: time to conclude the exploration task; and time interval between two consecutive sensing of any specific region. According to US strategy, a discrete random variable, defined by a uniform distribution in the space of the angles A_s, determines the steering direction adjustments. Observe that there is no connection between the pheromone and the uniform strategy; different from the SS and BRSS strategies.

The environment designed for evaluation is such as in Figure 3. It is possible to identify six rooms. Three robots k, $k \in \{1, 2, 3\}$, start the navigation at the room 1.

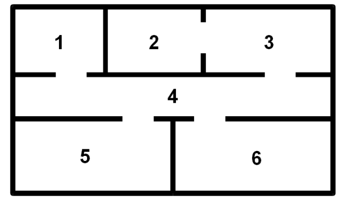


Figure 3. Environment structure

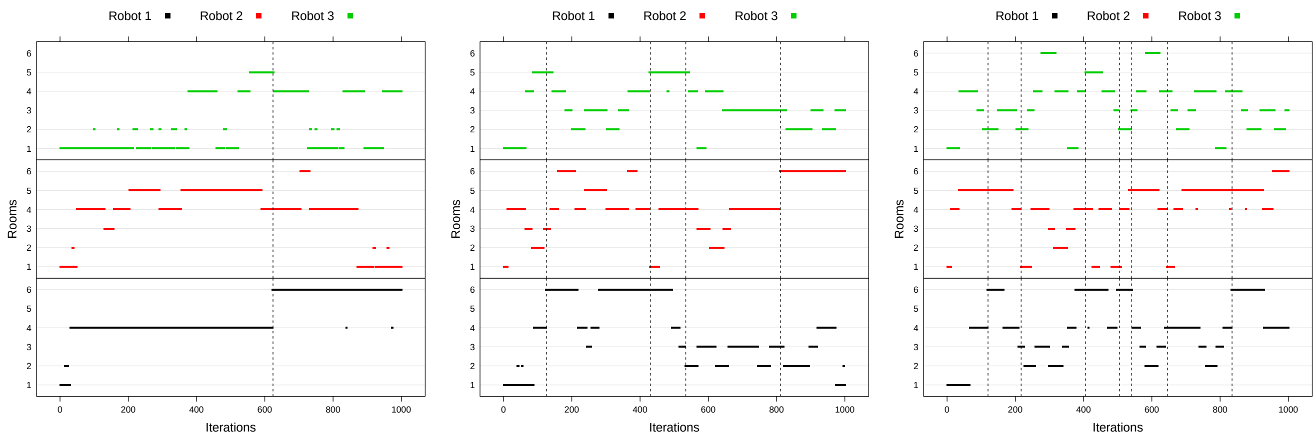
The performance of IAS-SS system according to mechanisms for adjustment of steering direction. Two aspects are considered for analysis: the time necessary to conclude the exploration task (SE); and maximum time interval between two consecutive sensing of any specific region (SI). The data are in Table I with the respective standard deviation for the average of number or SE and the average of SI considering 10 trials for each experiment. The performance of IAS-SS system is improved gradually as shown in graphic of Figure 4. It shows the boxplots of average of surveillance intervals of three mechanisms. The numbers 1, 2 and 3 refer to US, SS and BRSS mechanisms, respectively.

Table I
PERFORMANCE OF MECHANISMS FOR ADJUSTMENT OF STEERING DIRECTION

Mechanism	Average of Number of SE	Average of SI (iterations)
US	0.28 ± 0.5	796 ± 395.68
SS	4.28 ± 1.11	233.26 ± 82.43
BRSS	7.25 ± 1.71	122.13 ± 24.57

Additional information about the behavior of the system can be gathered observing the Figure 5. It exhibits three sets of graphics that summarize the simulation conducted, each of which corresponding to a different strategy. Data used to plot the graphics are from the trial with the median number of SI. For each strategy, three graphics are presented, each of which registering the behavior of one of the robots. The y-axis represents the rooms and the x-axis represents the iterations. Each vertical line indicates the SE, that is, the iteration when IAS-SS senses the whole environment (the robots visit cooperatively all the 6 rooms), considering that a new sense task is started after the system concludes the earlier one.

Considering the exploration task, the graphics show that the IAS-SS system with the Uniform Strategy is able to conclude the exploration task, but after a long time, precisely at the iteration 624. Observe that with strategies SS and BRSS the IAS-SS system executes more efficiently the task, that is, the system concludes the task very earlier, at the iterations 126 and 120, respectively. The IAS-SS system with US strategy concludes the surveillance task only once (there



(a) (b) (c)

Figure 5. IAS-SS performance according to different strategies: (a) US; (b) SS; (c) BRSS mechanism.

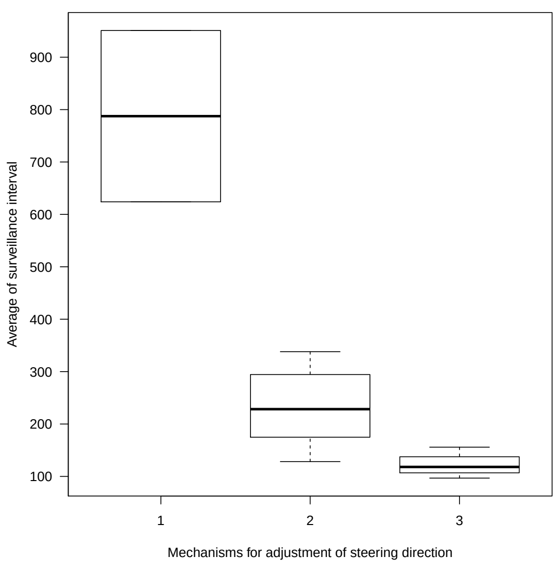


Figure 4. Boxplots of distibution of the average of surveillance intervals for differents mechanisms for adjustment of steering direction

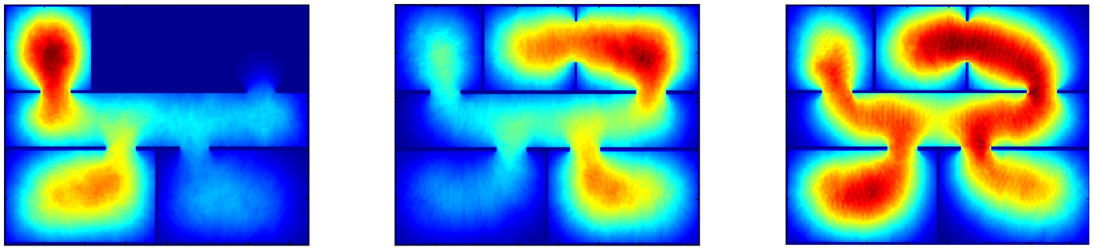
is only one SE), considering all the simulation. There is a strong contrast if this performance is compared with those obtained with the strategies SS and BRSS. Vertical lines indicate that the system with these strategies continually concludes the surveillance tasks (all the robots cooperatively visit the 6 rooms).

Pheromone distribution in an environment is an evidence of efficiency of strategy. The IAS-SS strategy is more efficient if the distribution of amount of pheromone is more egalitarian in entire environment. In this case, the average of amount of pheromone in all environment composes the map of pheromone distribution. It indicates the frequency when a specific region was visited (or monitored) in relative to others. To comprehension of map, regions with low amount of pheromone are represented by blue color, whereas red color denotes regions with high amount of pheromone (or visitation frequency higher). Hence, to comprove the best performance of strategy when BRSS mechanism is adopted, Figure 6 shows the average of amount of pheromone for mechanisms of adjustment of steering direction. According to the same data used to plot the graphics of Figure 5, the pheromone distribution is more uniform for BRSS strategy (Fig 6(c). In constrast, it can be noted that more amount of pheromone in rooms 1 and 5 for execution of US strategy (Figure 6(a)).

These data are summarized in the Tables II and III. The system with SS strategy concludes the surveillance task 4 times and BRSS 7 times, and the maximum intervals between two consecutive conclusions are 304 and 189 iterations, respectively. The IAS-SS system with BRSS is clearly superior. The strategies SS and BRSS induce a stronger collaborative robot behavior than in the case of US strategy. Observe that robots in the pheromone dependent strategies vary more the rooms that they visit than robots do in the case of US strategy.

B. Initial position of robots

This group of experiments evaluates the efficiency of IAS-SS for distinct configuration of robots regards as their positions. Two cases of configuration of robots are designed in order to analyze the performance system: **1) together configuration** robots start navigation at same region (or room) and **2) separated configuration** at distinct rooms. For exploration and surveillance tasks, it is obvious the greater efficiency is guaranteed when the robots are not closer. However, experiments intend to demonstrate that, after a while, scenarios of joint configuration can achieve the same efficiency of separated configuration. Experiments to verify



(a) (b) (c)

Figure 6. Maps of average of amount of pheromone according to strategies: (a) US; (b) SS; (c) BRSS.

Table II
SURVEILLANCE EPOCH FOR STEERING DIRECTION MECHANISMS

Mechanism	Max. SI (iterations)	Surveillance Epoch (iterations)						
		1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}	7^{th}
US	624	624	—	—	—	—	—	—
SS	304	126	304	104	277	—	—	—
BRSS	189	120	97	189	99	36	105	189

Table III
MONITORED ROOMS AT EACH SURVEILLANCE EPOCH

Mechanism	Robot	Monitored Rooms						
		1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}	7^{th}
US	# 1	1,2,4,6	—	—	—	—	—	—
	# 2	1,2,3,4,5	—	—	—	—	—	—
	# 3	1,2,4,5	—	—	—	—	—	—
SS	# 1	1,2,4,6	6,4,3	6,4,3,2	2,3	—	—	—
	# 2	1,2,3,4	3,4,6,5,1	1,4	4,3,2,6	—	—	—
	# 3	1,4,5	5,4,3,2	5,4	5,4,3,1	—	—	—
BRSS	# 1	1,4,6	6,4,3	3,2,4,6	6,4	6	6,4,3,2	4,3,2,6
	# 2	1,4,5	5,4,1	1,4,3,2	4,1	1,4,5	5,4,1	1,4,5
	# 3	1,4,3,2	2,3	2,3,4,6,1,5	5,4,3,2	2,3	3,4,6	4,3,2,1

the performance according to initial position of robots is accomplished in environment of Figure 7. For both of cases of configuration, three robots are launched. In particular for separated and together configurations, they start navigation at rooms 2, 6 and 7; and room 1, respectively.

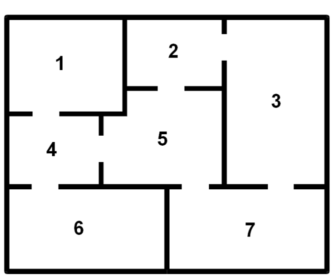


Figure 7. Environment structure

For the next experiments, six environment configurations are generated from combination of cases of configurations (separated and together) and steering direction mechanisms of experiments of Section V-A. Analogously to the previous experiments, two aspects are considered for analysis of the performance of IAS-SS system. As can be seen in the Table IV, the separated configuration with SS mechanism yields the best performance, regarding both number of SE (nb. of SE) and average of SI (av. of SI). In the case of together configuration, the best results are obtained with the BRSS mechanism, which is, in fact, the best overall strategy. The Figure 8 shows the boxplots of the surveillance intervals of the six environment configurations. The numbers 1,. . ., 6 refer to environment separated configuration with US, SS and BRSS mechanism; and environment together configuration with US, SS and BRSS mechanisms, respectively.

The key of surveillance task is minimizing the time (iterations) which a region is non-monitored. Hence, here, a manner to measure the system performance is to analyze the maximum period (maximum number of iterations) which each room is non-visited. Maximum periods that rooms are non-visited are presented in Figure 9 for the six environment configurations. Data used to plot the graphics are from the trial with the median of average of number of SE and average of SI. Although separated configuration presents slightly advantage over together configuration, since at iteration $t = 0$, three robots monitor three different rooms, the performances of both configurations are similar. One of main characteristics of IAS-SS system is the skill of

Table IV
PERFORMANCE OF ENVIRONMENT CONFIGURATIONS WITH MECHANISMS FOR ADJUSTMENT OF STEERING DIRECTION

Configuration	Uniform Sampling	
	nb. of S.E.	av. of SI.
Separated	1 ± 0.94	358.55 ± 272.67
Together	0.43 ± 0.53	247 ± 313.77

Configuration	Stochastic Sampling	
	nb. of S.E.	av. of SI.
Separated	6.66 ± 1.73	160.04 ± 85.65
Together	6 ± 2.16	185.03 ± 122.4

Configuration	Best Ranked Stochastic Sampling	
	nb. of S.E.	av. of SI.
Separated	6 ± 2	199.71 ± 101.62
Together	7.85 ± 2.61	120.51 ± 44.3

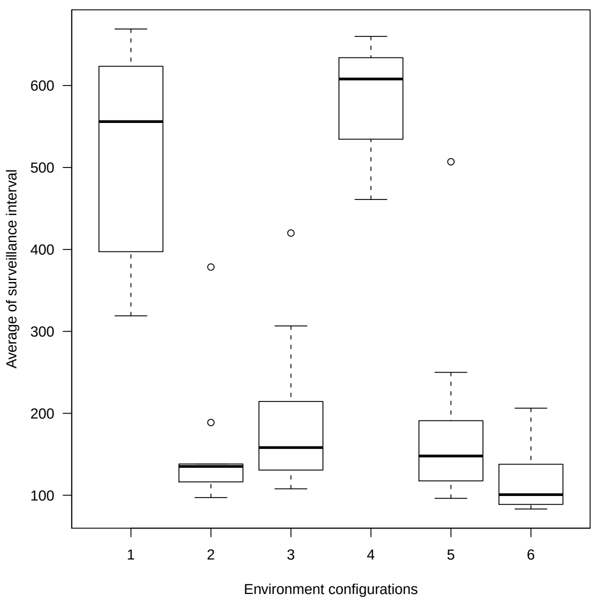


Figure 8. Boxplots of distribution of the average of surveillance intervals for the different adjustment of steering direction mechanisms

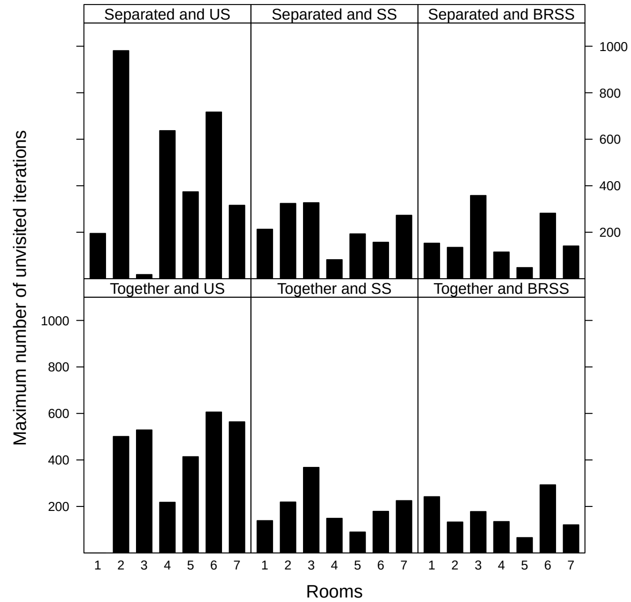


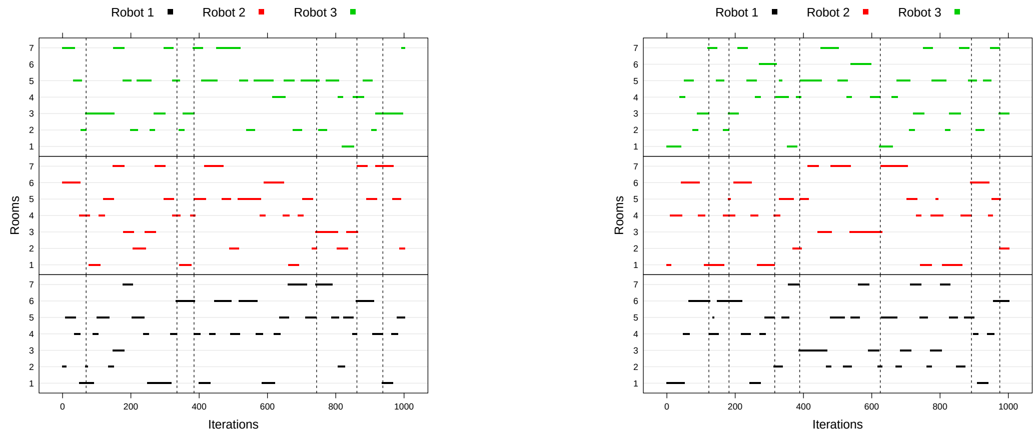
Figure 9. Maximum number of non-visited rooms iterations

robots to keep distance from each other according to aversive pheromone. Then, even with together configuration, as long the robots move, they are spread in environment. Thus, the performance of together configuration becomes similar to separated configuration. That is, the advantage of separated configuration is diluted during navigation. To illustrate this scenery, graphics of Figure 10 show the behavior of robots and surveillance intervals for separated and together configurations using BRSS mechanism. They show that the IAS-SS system with the separated configuration concludes the SE task 6 times while the together configuration takes 7 times.

The next set of experiments investigates how the environment scale parameter influences the performance of the IAS-SS strategy. Two environments are considered, Both present the same layout of the environment of Figure 7, but with different sizes. The first is 2 times larger than that environment, while the second is 3 times. The environment used in previous experiments and the two newly defined are called here environments x1, x2 and x3, respectively. The motivation to enlarge the scale of the environment is to asses the suitability of the strategy in sensing all parts of the rooms.Differently from experiments of environment x1, the number of iterations for experiments with environments x2 and x3 are 2000 and 3000, respectively.

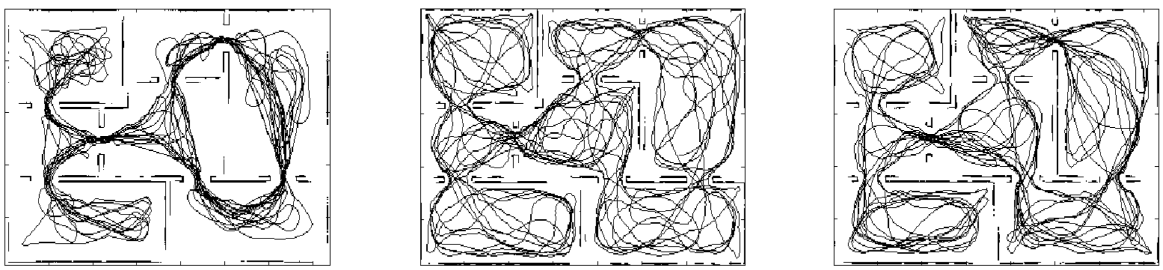
The self-adapt trait of the system is visualized through the trajectories of robots of Figure 11. Only the obtained trajectories from simulation of experiments that consider BRSS mechanism and together configuration the are showed in order to contrast the slight difference of performed paths. It can observed that the trajectories are concentrated in a trail when the rooms are small (Figure 11(a)). An explanation for this outcome is the small size of rooms. In this case, the sensor range covers the whole room as the robot enters in the room. While for large regions resultant from environments with duplicated and triplicated scale, the robots move away from the trail to cover the entire environment efficiently (Figures 11(b) and 11(c)). The data presented are from the trial with the median number of SI for each environment configuration.

Analogously to the experiments regarding environment x1, the performances of separated and together configurations for environments x2 and x3 are similar. This is justified by repulsive characteristic of pheromone, which keeps the robots far from each other after while independently of the adopted configuration (separated or together). The Tables V and VI corroborate that there is no strong contrast among



(a) (b)

Figure 10. IAS-SS performance according to different configurations for BRSS: (a) separated; (b) together configurations.



(a) (b) (c)

Figure 11. Trajectories of robots during exploration and surveillance tasks for experiments with BRSS mechanism and together configuration: (a) environment x1; (b) environment x2; (c) environment x3.

of performances of separated and together configurations. Regarding the adjustment of steering mechanisms, those configurations with BRSS mechanism yield the best performance when the average of number of SE and average of SI are compared to other mechanisms. The performance of IAS-SS system for the six environment configuration is shown in graphics of Figure 12. The numbers 1,. . ., 6 refer to environment separated configuration with US, SS and BRSS mechanisms; and environment together configuration with US, SS and BRSS mechanisms, respectively.

Maximum periods that rooms are non-visited in experiments of environments x2 and x3 are presented in Figures 13(a) and 13(b), respectively, for the six environment configurations. Data used to plot the graphics are from the trial with the median of average of number of SE and average of SI. It can be noted that regardless which configuration is employed, the system performance improves as long as the mechanism for adjustment of steering direction changes from US to BRSS. The behavior of robots and surveillance intervals for separated and together configurations using BRSS mechanism is clarified in graphics of Figures 14 (environment x2) and 15 (environment x3). For the environment x2, the IAS-SS system with the separated configuration concludes the SE task 9 times and whit the together configuration takes 8 times. While for the environment x3, the SE task is conclude 5 times with the separated configuration and 6 times using the together configuration.

Table V
PERFORMANCE OF ENVIRONMENT CONFIGURATIONS WITH MECHANISMS FOR ADJUSTMENT OF STEERING DIRECTION FOR ENVIRONMENT X2

Configuration	Uniform Sampling	
	nb. of S.E.	av. of SI.
Separated	2.16 ± 0.75	892 ± 517
Together	1.75 ± 0.95	985.75 ± 576.36
Configuration	Stochastic Sampling	
	nb. of S.E.	av. of SI.
Separated	5.2 ± 1.62	352.72 ± 131.96
Together	4.6 ± 2.01	325.11 ± 94.15
Configuration	Best Ranked Stochastic Sampling	
	nb. of S.E.	av. of SI.
Separated	8.1 ± 2.47	246.8 ± 68.33
Together	8.3 ± 1.88	226.1 ± 59.48

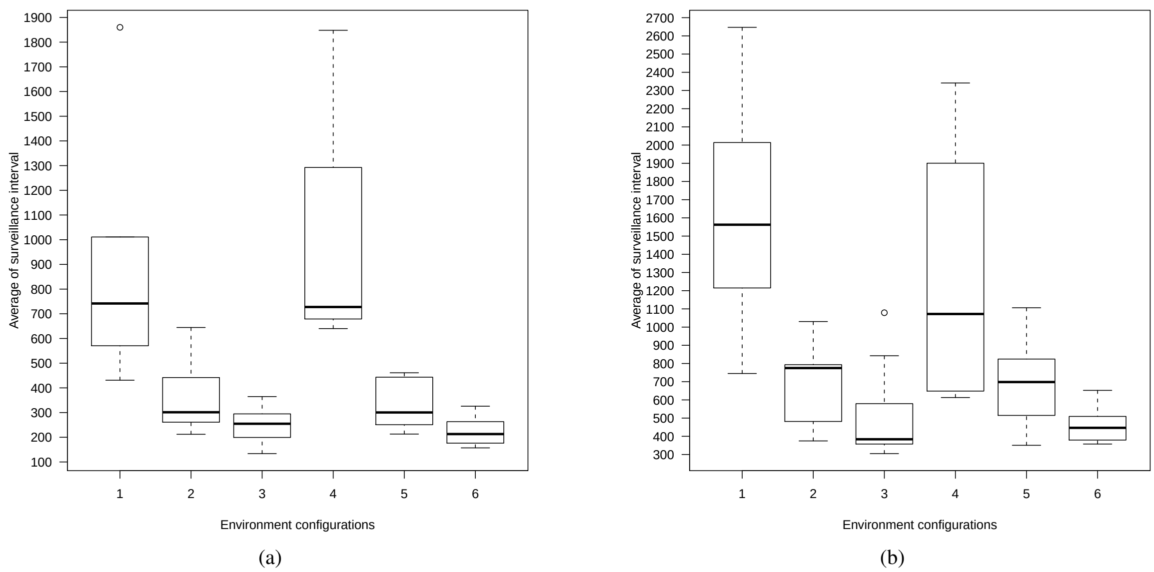


Figure 12. Boxplots of distribution of the average of surveillance intervals for the different adjustment of steering direction mechanisms for: (a) environment x2; (b) environment x3.

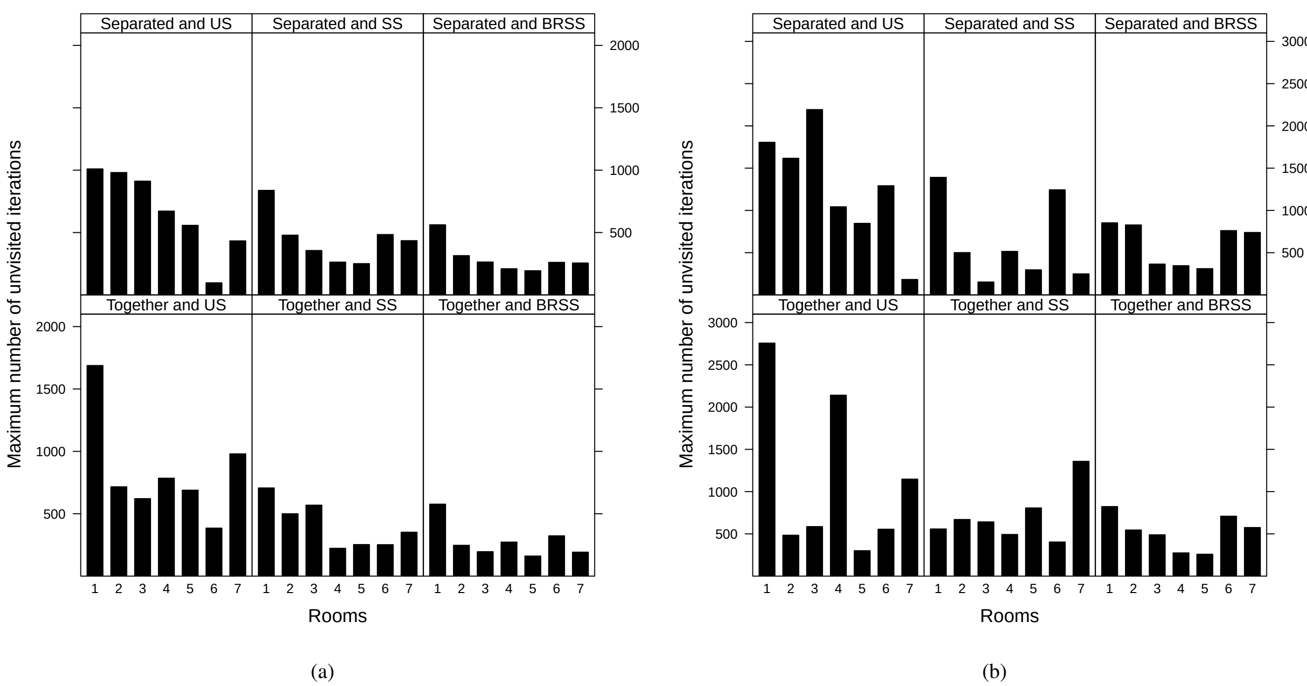
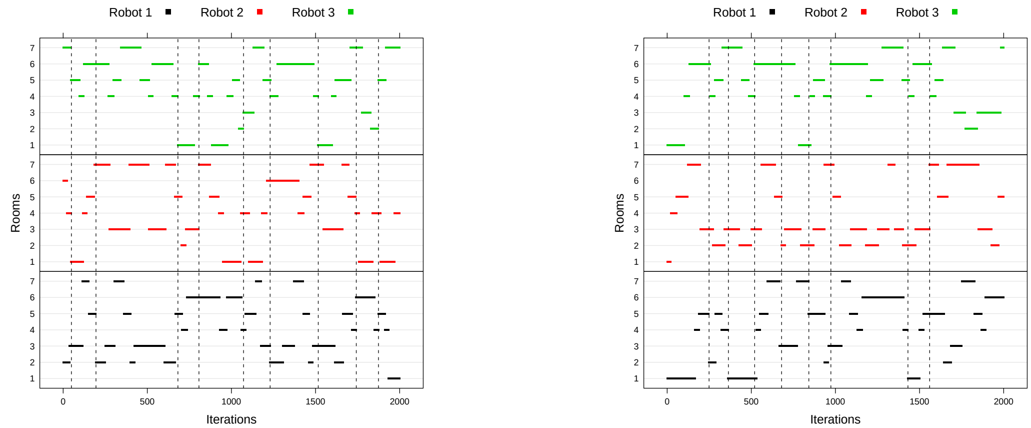
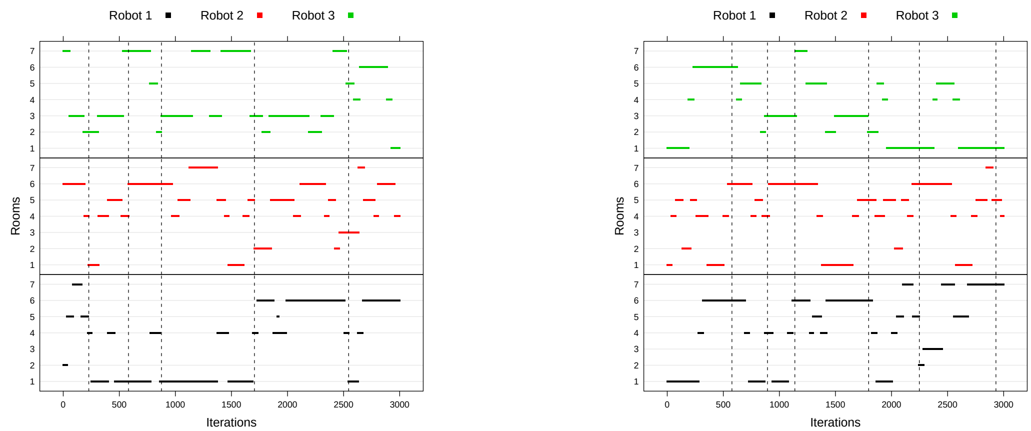


Figure 13. Maximum number of non-visited rooms iterations for: (a) environment x2; (b) environment x3.



(a) (b)

Figure 14. IAS-SS performance according to different configurations for BRSS in environment x2: (a) separated; (b) together configurations.



(a) (b)

Figure 15. IAS-SS performance according to different configurations for BRSS in environment x3: (a) separated; (b) together configurations.

Table VI
PERFORMANCE OF ENVIRONMENT CONFIGURATIONS WITH MECHANISMS FOR ADJUSTMENT OF STEERING DIRECTION FOR ENVIRONMENT X3

Configuration	Uniform Sampling	
	nb. of S.E.	av. of SI.
Separated	1.37 ± 0.52	1621.87 ± 610.53
Together	1.5 ± 0.57	1274.5 ± 808
Configuration	Stochastic Sampling	
	nb. of S.E.	av. of SI.
Separated	4.33 ± 1.11	675.8 ± 211.17
Together	3.5 ± 1.27	685.28 ± 239.51
Configuration	Best Ranked Stochastic Sampling	
	nb. of S.E.	av. of SI.
Separated	5.44 ± 1.51	519.2 ± 269
Together	6.7 ± 4.47	460.5 ± 100.11

C. *Environment Structure*

One of characteristic if IAS-SS strategy is the self-adapt. It is emphasized in this section. Following experiments aim at analyzing the performance of exploration and surveillance tasks independently of environment structure. To investigate this characteristic, distinct environment structures are designed from a rectangular space divided virtually in 10 rooms as illustrated in Figure 16(a). The connectivity among adjacent rooms is represented by a graph (Figure 16(b)). Accesses that connect rooms are partially or totally blocked by obstacles, generating different environments. According to this process, ten models of environment are considered, such that, each environment is associated to a complexity level.

Complexity level is measured according to number of options to travel the environment (among rooms), that is, through graph structure resultant from connection among rooms. The more path options to reach a specific region are available, the complexity level of environment is higher. For environments of Figures 16(c) and 16(d), the graph structure is the same of the graph of Figure 16(b), hence, the com-

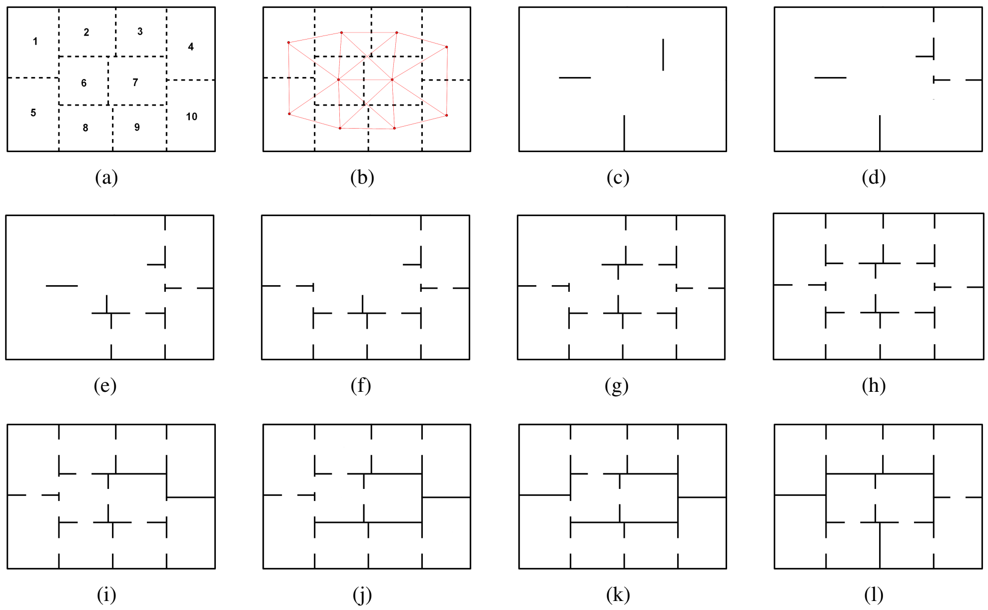


Figure 16. Environment models: (a) environment divided in rooms; (b) connection graph amoung rooms; (c)-(l) environment from #1 to #10.

plexity is low. As obstacles are inserted into environments blocking the passage amoung rooms, the respective edges of graph are removed and, thus, the complexity is higher.

Since there are ten rooms, four robots are considered for experiments to assign at least two rooms to each robot. This forces the robots travels long distances increasing the likelihood find challenging situations as obstacles. All robots start at room 1.

Although it is clear that the exploration time decreases as complexity level increases, the surveillance task is accomplished even with a restricted number of path options. This emphasizes that environment structure is not a factor that impedes the tasks to execute. Even robots in environments with higher complexity level can carry out the tasks. The environment sensing (SE) is completed independently of the environment structure. As general behavior of the system, the length of SI period is increased while the complexity level of environment increases. Also, as consequence of the higher complexity, the number of completed SE is smaller. This can be observed in Table VII. The average of number of SE increases and the average of SI presents a strong decreasing tendency, which is not monotonic due to the random nature of experiments. Therefore, it is observed that the system self-adapt according to changes in the environment model. A more detailed view of results of table, regarding the average of SI, is presented in the Figure 17. It shows the boxplots of the distribution of the performance.

The self-adapt trait of the system is visualized through the trajectories of robots and maps of average of amount of pheromone of Figure 18 for some environment models in order to contrast the high difference of complexity level among them. It can observed that the trajectories are concentrated in a trail when the rooms are small. An explanation for this outcome is the small size of rooms. In this case, the sensor range covers whole the room. While for large regions resultant from junction rooms in environments #1 and #3, the robots move away from the trail to cover the entire environment efficiently. The data presented are from the trial with the median number of SI for each environment.

Table VII
PERFORMANCE OF CONFIGURATION WITH BRSS MECHANISM AND INCREASING THE COMPLEXITY LEVEL

Environment	Number of SE	Average of SI
#1	17 ± 3	57.46 ± 10.41
#2	15.66 ± 2.08	61.9 ± 7.83
#3	13.66 ± 0.57	70.76 ± 6.27
#4	15 ± 2	63.77 ± 8.91
#5	12.66 ± 1.52	77.29 ± 11.58
#6	11 ± 1.73	87.65 ± 19.59
#7	9 ± 0.01	97.75 ± 7.7
#8	7.66 ± 57.73	114.17 ± 23.82
#9	7.66 ± 57.73	119.49 ± 3.88
#10	7.33 ± 1.52	115.23 ± 24.9

D. Number of robots

This section discusses about the relation between the size of environment and number of robots. Indeed, higher number of robots is, more regions are explored and monitored simultaneously, so that, few or no regions are empty for long period. Since robots behavior is based on inverse of ant algorithm, the probability of one robot explorer and monitor large environments is higher. However, it may take a long time. In order to evaluate the performance of motion coordination and the efficiency of surveillance task, experiments are carried out with an increasing number of

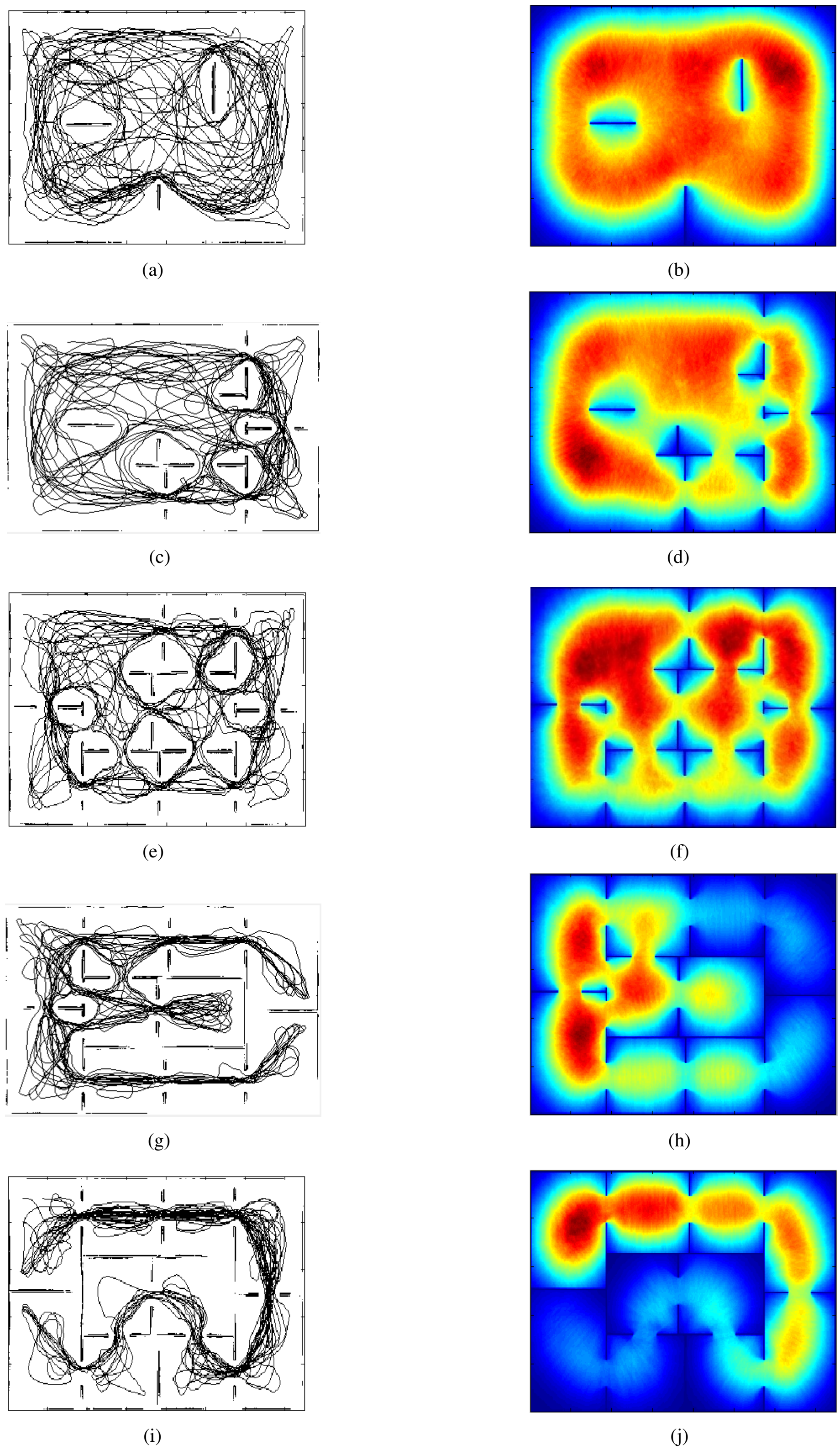


Figure 18. Trajectories of robots and maps of average of amount of pheromone according to distinct environment strutures: (a)-(b) #1; (c)-(d) #3; (e)-(f) #5; (g)-(h) #8; (i)-(j) #10.

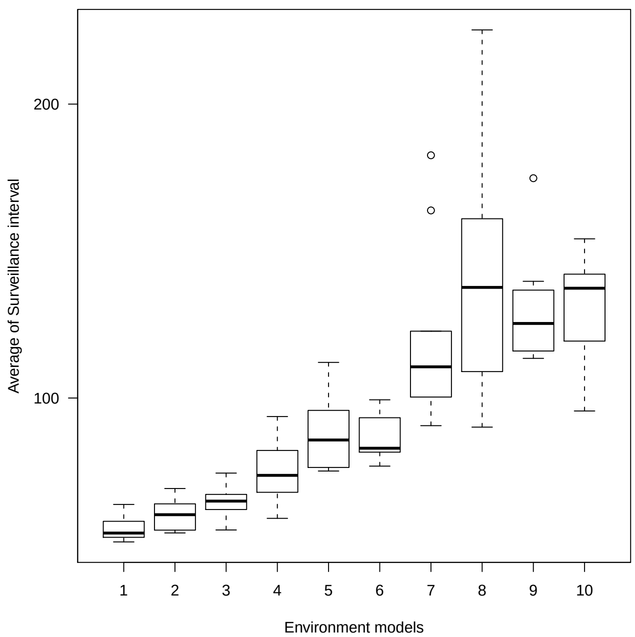


Figure 17. Boxplots of distribution of the average of surveillance intervals for different degree of complexity of environment.

robots in environment of Figure 19. Since BRSS mechanism presented better performance than US and RS mechanisms in previous experiments, this mechanism is adopted to analyze the efficiency of the exploration and surveillance tasks while the number the robots increases. All added robots are placed at room 1.

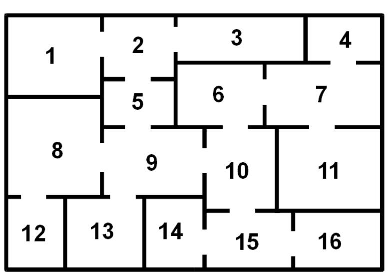


Figure 19. Environment structure

Although it is clear that the time to explore decreases as number of robots increases, the surveillance task is accomplished even with a restricted number. This emphasizes that number of robots is not a factor to limit the size of the explored environment. Even few robots are able to monitor large areas. The environment sensing (SE) is completed independently of the number of robots. However, as general behavior of system, the length of SI period is reduced while the number of robots increases. Also, as consequence of the addition of robots, there are more completed SE. This can be observed in Table VIII. As the number of robots increases, the average of number of SE increases together. Conversely, the average of SI presents a strong decreasing tendency, which is not monotonic due to the aleatory nature of experiments. Therefore, it is observed that the system self-adapt according to the number of robots. A more detailed view of results of table, regarding the average of SI, is presented in the Figure 20. It shows the boxplots of the distribution of the performance for the 10 trials.

Table VIII
PERFORMANCE OF TOGETHER CONFIGURATION WITH BRSS MECHANISM FOR INCREASING NUMBER OF ROBOTS

Number of robots	Number of SE	Average of SI
2	0.5 ± 0.7	598.25 ± 196.62
3	1.1 ± 0.57	621.44 ± 179.88
4	1.5 ± 0.97	412.56 ± 190.89
5	1.5 ± 0.97	504.77 ± 239.93
6	2.4 ± 0.51	220.60 ± 65.26
7	3.2 ± 0.78	174.01 ± 58.25
8	3.4 ± 0.98	155.97 ± 59.30
9	3.9 ± 1.28	137.94 ± 61.57
10	5.3 ± 1.5	118.75 ± 20.92
11	5.7 ± 2	115.98 ± 44.14
12	6.4 ± 1.89	107 ± 38
13	6.9 ± 2.42	108.4 ± 46.47
14	8.2 ± 1.68	88.04 ± 21.93
15	8.3 ± 2.78	92.02 ± 40.23

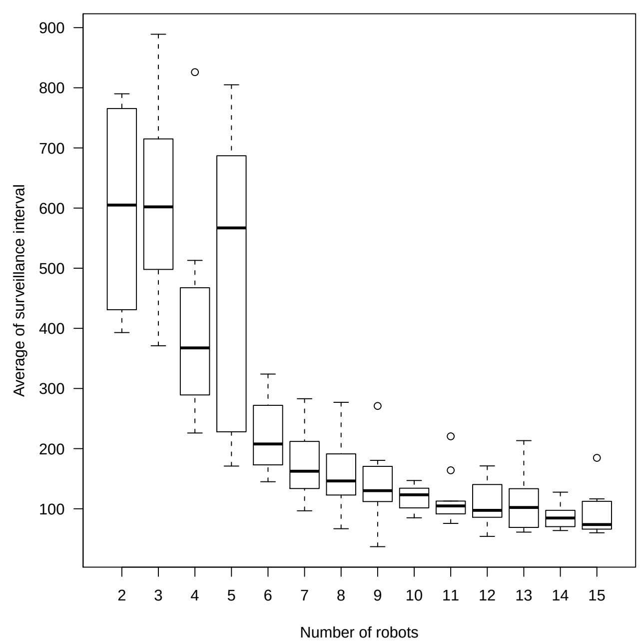


Figure 20. Boxplots of distribution of the average of surveillance intervals for the different mechanisms for adjustment of steering directions

The experiments performed are to show that the autonomous proposal gets to execute the surveillance task satisfying the constraints set up in the equation 2. However, the minimization of the objective function is not considered here. In this step, the work is only to verify the surveillance capability.

E. For Real Robots

For the validation of IAS-SS strategy in a real robots plataform, two approaches are suggested. The first one is to equip physical robots with devices for releasing some chemical and odour sensors. As long as the robots navigate, they left this substance in the frontal regions to mark them as explored regions. Through odour sensors, the robots are able to detect the regions more attractive, i.e., the regions with low amount of the substance. The second one only considers distance sensors, disgarding the presence of the odour sensors. Then, applying the mapping method, occupancy-grid, as mentioned in Section V, the generated cells could be used for hosting a value that indicates the amount of deposited pheromone. Hence, the amount of pheromone would exist in a virtual way. The virtual pheromone releasing and detecting areas correspond to the range area of the distance sensors. However, in the last approach, a localization method [34] would be need in order to each robot to built its own local map and, accordingly, to join it with the local maps of another robots. Thus, using less sensors, the strategy is able to explore the entire environment and to perform the surveillance task. The implementation in real robots makes part of future works.

VI. Conclusions and Future Works

In this work, it was proposed a new bio-inspired distributed coordination strategy, named IAS-SS, for multiple robot systems applied for exploration and surveillance tasks. The strategy is based on swarm theory, specifically the ant system theory. The repulsive character as a function of the deposited pheromone quantity determines the dynamic of behavior of the agents (robots) and stimulates them to be spread out by the environment. As a consequence, the agents get to monitor the entire environment continuously, visiting regions not recently visited. Furthermore, other contributions can be highlighted, such as, the development of a decentralized strategy, where the robots are independent agents that define their steering direction without an extern influence; a reactive strategy, in which the only information necessary for the robots is extracted from amount of pheromone and, finally, a pheromone trail is not generated, since the deposit of pheromone occurs only in areas covered by distance sensors (i.e., frontal areas to the robot).

Although the strategy is very simple compared to other environment exploration strategies, both exploration and surveillance tasks were efficiently performed. A set of experiments were done for analising the performance of the proposed system. Experiments considered two performance criteria: the average of the numbers of surveillance epochs and average of the surveillance time intervals. Four parameters, namely: start position, number of robots, environment scale and environment structure; stress the strategy capabilities. Two versions of the IAS-SS strategy were considered and compared with a totally random strategy. The IAS-SS strategies presented significantly a superior performance. Some characteristics of these strategies were noted, such as, they are not dependent on the knowledge of the environment structure and they are robust in regard to the number of robots. These strategies kept robots well separated guiding them toward regions not recently visited. The advantage of the bioinspired strategy proposed resides in, among other aspects: simple conceptual ideas, reduced computation complexity, real time operation and efficiency.

It is important to say that calculate the complexity of proposed algorithm is a tedious task. Since the performance criterium is the number of SE and average of SI, the obtained results present distinct perfomance due to changes of structure of environments, number of robots and initial position configuration. Therefore, there are many combinations to establish the coordination strategy. In addition, the approaches about monitoring found in literature emphasize graphs to define the routes of robots. Therefore, there is no approach similar to the present proposal in order to summarize a suitable comparison of complexity.

As future works experiments will be designed to investigate two aspects: how different pheromone releasing mechanisms influence the performance of the IAS-SS system; and to investigate the adaptation capability when some robots fail. Moreover, a method to join maps will be conceived and integrated to IAS-SS system in order to apply it in real robots. Thus, it is need to develop a communication device to support change information about mapping. This device, coupled to robots, will able to identify other robots and transfer data through wireless network. In addition, more complex surveillance tasks, e.g., those that a strange agent invades the environment, will be investigated. In this case, a vision system with tracking ability is essential.

Acknowledgment

The authors would like to thank Sao Paulo Research Foundation (FAPESP) and National Council for Scientific and Technological Development (CNPq) for their support.

References

[1] R. Calvo, J. R. de Oliveira, M. Figueiredo, and R. A. F. Romero. "Inverse ACO Applied for Unknown Environment Exploration". In: The Third International Conference on Advanced Cognitive Technologies and Applications, 2011, Rome, Italy. Proceedings of COGNITIVE'2011, p. 142-147, 2011.

[2] J. G. Bellingham, and M. Godin, "Robotics in Remote and Hostile Environments". Science, vol. 318, pp. 1098-1102, 2007.

[3] H. H. Schmitt, "From the Moon to Mars". Nature, vol. 301, pp. 36-43, 2009.

[4] F. Mazzini, D. Kettler, J. Guerrero, and S. Dubowsky. "Tactile Robotic Mapping of Unknown Surfaces, With Application to Oil Wells". IEEE Transactions on Instrumentation and Measurement, vol. 60, pp. 420-429, 2011.

[5] X. L. Long, J. P. Jiang, and K. Xiang. "Towards Multirobot Communication". IEEE International Conference on Robotics and Biomimetics, 2004. ROBIO 2004, pp. 307-312, 2004.

[6] A. Speranzon. "Coordination, Consensus and Comunnication in Multi-Robot Control Systems". PhD Thesis, Royal Institute of Technology, Stockholm/Sweden, 2006.

[7] C. Liu, Y. Ma, and C. Liu. "Cooperative Multi-robot Map-Building Under Unknown Environment". Proceedings of the 2009 International Conference on Artificial Intelligence and Computational Intelligence, vol. 3, pp. 392-396, 2009.

[8] L. Andersson, and J. Nygårds. "On Multi-robot Map Fusion by Inter-robot Observations". In proceedings of 12th International Conference on Information Fusion, 2009.

[9] B. Yamauchi. "A frontier-based approach for autonomous exploration". Proceedings of the 1997 IEEE International Symposium on Computational Intelligence in Robotics and Automation, pp. 146-151, 1997.

[10] F. Pasqualetti, A. Franchi, and F. Bullo. "On optimal cooperative patrolling". IEEE Conf. on Decision and Control, Atlanta, GA, USA, pages 7153-7158, December 2010.

[11] D. Scheidt, and J. Stipes. "Cooperating unmanned vehicles". Proceedings of the 2005 IEEE Networking, Sensing and Control, pp. 326-331, 2005.

[12] J. Stipes, R. Hawthorne, D. Scheidt, and D. Pacifico. "Cooperative Localization and Mapping". Proceeding of the IEEE, Networking, Sensing and Control, pp. 596-601, 2006.

[13] A. Marjovi, J. G. Nunes, L. Marques, and A. de Almeida. "Multi-robot exploration and fire searching". Proceedings of the 2009 IEEE/RSJ international conference on Intelligent robots and systems, pp. 1929-1934, 2009.

[14] A. Howard, M. J. Mataric, and G. S. Sukhatme. "Mobile Sensor Network Deployment using Potential Fields: A Distributed, Scalable Solution to the Area Coverage Problem". Proceeding of the 6th International Symposium on Distributed Autonomous Robotics Systems, pp. 299-308, 2002.

[15] J. Tan, N. Xi, W. Sheng, and J. Xiaov. "Modeling multiple robot systems for area coverage and cooperation". Proceedings of the 2004 IEEE International Conference on Robotics and Automation, pp. 2568-2573, 2004.

[16] Q. Jiang. "An improved algorithm for coordination control of multi-agent system based on r-limited voronoi partitions". Automation Science and Engineering, 2006. CASE '06. IEEE International Conference on, pp. 667-671, 2006.

[17] F. WeiXing, W. KeJun, Y. XiuFen, and G. ShuXiang, "Novel Algorithms for Coordination of Underwater Swarm Robotics", *Proc. of IEEE Int. Conf. on Mechatronics and Automation*, pp. 654-659, 2006.

[18] R. A. Freeman, P. Yang, and K. M. Lynch, "Distributed estimation and control of swarm formation statistics", *American Control Conf.*, 7 pp. 749-755, 2006.

[19] F. Kobayashi, N. Tomita, and F. Kojima, "Re-formation of mobile robots using genetic algorithm and reinforcement learning", *SICE 2003 Annual Conf.*, vol. 3, pp. 2902-2907, 2003.

[20] L. Barnes, W. Alvis, M. A. Fields, K. Valavanis, and W. Moreno, "Swarm Formation Control with Potential Fields Formed by Bivariate Normal Functions", *14th Mediterranean Conf. on Control and Automation*, pp. 1-7, 2006.

[21] J. M. Hereford, "A Distributed Particle Swarm Optimization Algorithm for Swarm Robotic Applications", *Proc. of IEEE Congress on Evolutionary Computation*, pp. 1678-1685, 2006.

[22] M. Hess, M. Saska, and K. Schilling, "Formation driving using particle swarm optimization and reactive obstacle avoidance", *Proc. of 1st IFAC Workshop on Multivehicle Systems (MVS)*, pp. 32-37, Lisboa, Portugal, 2006.

[23] M. Dorigo, M. Birattari, and T. Stützle. "Ant Colony Optimization Artificial Ants as a Computational Intelligence Technique". IEEE Comput. Intell. Mag, pp. 28-39, 2006.

[24] R. Calvo, J. R. de Oliveira, M. Figueiredo, and R. A. F. Romero. "A Distributed, Bio-Inspired Coordination Strategy for Multiple Agent Systems Applied to Surveillance Tasks in Unknown Environments". In: International Joint Conference on Neural Networks, 2011, San Jose, CA, USA. Proceedings of IJCNN'2011. Los Alamos : IEEE Press, p. 3248-3255, 2011.

[25] R. Calvo, J. R. de Oliveira, M. Figueiredo, and R. A. F. Romero. "Bio-inspired coordination of multiple robots systems and stigmergy mechanisms to cooperative exploration and surveillance tasks". In: IEEE 5th International Conference on Cybernetics and Intelligent Systems and on Robotics, Automation and Mechatronics, 2011, Qingdao, China. Proceedings of CIS-RAM'2011, p. 223-228, 2011.

[26] M. Dorigo. "Optimization, learning and natural algorithms". PhD thesis, Dipartimento di Elettronica, Politecnico di Milano, 1992.

[27] E. Bonabeau, M. Dorigo, and G. Theraulaz. "Inspiration of optmization from social insect behavior". Nature, pp. 39-42, 2000.

[28] M. Dorigo, G. Di Caro, and L. Gambardella. "Ant Algorithms for Discrete Optimization". Technical Report IRIDIA/98-10, Universite Libre de Bruxelles, Belgium, 1999.

[29] D. Yingying, H. Yan, and Jiang Jingping. "Multi-robot cooperation method based on the ant algorithm". Proceedings of the 2003 IEEE Swarm Intelligence Symposium, pp. 14-18, 2003.

[30] B. Christian. Review of "Ant colony optimization" by M. Dorigo, and T.Stützle, MIT Press, Cambridge, MA, 2004. Artif. Intell., pp. 261-264, 2005.

[31] L. A. Zadeh, "Fuzzy Sets", *Information and Control*, Vol. 8, 338–353, 1965.

[32] R. Calvo, M. Figueiredo, and R. A. F. Romero. Autonomous cognition and reinforcement learning. In: IEEE International Joint Conference on Neural Network, Barcelona, Spain. Proceedings of IJCNN'2010, p. 1-8, 2010.

[33] A. Elfes. ”Using Occupancy Grids for Mobile Robot Perception and Navigation”. Computer, issn 0018-9162, vol 22, pp. 46-57, Los Alamitos, CA, USA, 1989.

[34] S. Thrun, D. Fox, W. Burgard, and F. Dellaert. ”Robust Monte Carlo localization for mobile robots”. Artificial Intelligence. vol. 128, n. 1-2, pp. 99 - 141 2000.