A Bio-inspired Approach in Decision-making of Multiple Robots Applied on Partitioned Surveillance Task

Bruno Massaki Emori and Rodrigo Calvo
Department of Computer Science, State University of Maringa, 5790 Colombo Avenue, 87020-900, Maringa-PR, Brazil

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Abstract: This paper proposes a robot coordination strategy for surveillance task execution. The strategy is based on artificial ants behavior, both for non explored regions and areas already discovered by the robots. In a strategy already known, the robots are not capable to distinguish its own pheromone from the pheromone of the others. In the proposed strategy, the ability to distinct the substances causes the environment's partition. Experimental results shows the typical behavior of each strategy applied to different environments and show the superiority of the proposed strategy due to the environment partitioning.

1 INTRODUCTION

The use of multi-agent systems to achieve an objective can be justified by many aspects, for example: the inviability to develop a coordination system that involves all available and necessary resources to solve a complex problem; the possibility to decompose the problem into several other subproblems, which are solved simultaneously by individual agents; and the possibility to use agents of small complexity to perform simple tasks and when grouped are able to solve a more complex problem.

The use of multiple agents is adopted in application which the individual behavior of robots leads into the solution as a whole. In this case, the robots act cooperatively. Many approaches use this kind of system in real and virtual world applications. Examples of these applications are: surveillance tasks and monitoring (Krishnan, 2015), cloud computing or automation (Sun et al., 2013), scheduling problems (Adhau et al., 2013), optimal solution search problems (Liemhetcharat et al., 2015), rescue (Eoh et al., 2013) and tasks allocation (Robu et al., 2011).

Regarding the surveillance problem, some proposed systems of multiple robots are based on mathematical models of the environment, specifically, a graph. In this case, the environment's structure is known, as well as the positioning of each robot in the scene in any given moment (Portugal, 2013). Generally, this model is adopted in (Fazli et al., 2013) to develop an off-line surveillance system. Initially, strategic points from the environment are previously defined in order to maximize the covering area of the scene. Then, a sequence of algorithms is executed to reduce the graph's size and also the trajectory established by the robots. A model based on graphs is also adopted in (Anisi et al., 2010). The robots' trajectory is determined using heuristic algorithms. The authors present a mathematical analysis and prove that the surveillance problem is NP-complete. In (Wallar et al., 2015), air robots perform the surveillance task.

A coordination strategy has an important role in multi-agent systems, since it creates conditions for a synergistic behavior to emerge. If this kind of collaborative behaviors exists, then the agents achieve better results interacting with each other rather than acting alone. Without synergisms, the system is just a mere group of robots. In this sense, bio-inspired approaches based on stigmergic interactions (e.g., artificial ants system) has drawn the scientific community's attention (Xiang and Lee, 2008).

The multiple robots system investigated here was developed to deal with the surveillance task that differs from the techniques usually presented in the literature. In this case, the requirements that define the task are kept (the environment must be sensed repeatedly and indefinitely) and other, added: the environment must be virtually partitioned in disjointed regions (sectors) of same extension in quantity equivalent to the number of robots; and each robot must perform the surveillance task in one of these sectors.

The proposed coordination strategy, named as Par-

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titioned Surveillance System (PSS), is based on a modified artificial ants algorithm (Dorigo, 1992). The logic presented differs from the traditional one, the pheromone deposited by an agent has a repulsive property. This way, the agents tend to disperse throughout the environment, avoiding that two or more agents perform the surveillance task in the same area or in very close areas. Besides that, the strategy tends to guide the robots into areas with no recent visitation, due to the absence of the substance.

The strategy must partition the environment in sectors that will be occupied by each one of the robots. The robots, individually, will be able to define autonomously their sectors due to the adopted behavior when the pheromone is detected. Hence, the number of sectors in an environment is equal to the number of robots. The environment's partition favors the surveillance task fulfillment more efficiently.

Each robot is equipped with two kinds of sensors: one of them detects the pheromone released by the robot itself; the second one detects the pheromone released by the other robots.

The coordination is not dependent of the parameters that define an environment and no information about the position and direction of the robots. Experiments performed in different scenarios shows a general behavior of the robots, consisting in two phases: first, the robots develop a dispersion behavior, and then, each agent defines a restrictive sector to cover and sensor. Lastly, o system reaches a stability stage. In this instant, the surveillance task is performed following the desired requirements: the environment is totally and repeatedly sensed and virtually partitioned into small disjointed sectors, which each one is monitored by a robot.

The paper is structured as it follows. The proposed strategy is described in Section 2 as well as the models of the sensors used. In Section 3, the experiments and discussion about the obtained results in simulations are presented. Main contributions, relevant aspects and future works are presented in Section 4.

2 PARTITIONED SURVEILLANCE SYSTEM

The PSS strategy was developed to deal with exploration and surveillance tasks of unknown environments, according to the principles of the ants algorithm (Dorigo, 1992). Essentially, the system is based on multiple mobile agents able to take decisions of movement adjustment, individually, according to the stimuli from the environment.

The mentioned tasks are performed due to the robot's ability to deposit a substance, named pheromone, on the environment, to mark the regions which they visited (or monitored). This substance has a repulsive feature, i.e, the robots tend to avoid areas with pheromone concentration. That behavior causes the robots spreading out in the environment. Although the robots deposit only one kind of pheromone, each one is able to distinguish its pheromone, (own pheromone) from the one deposited by the others (odd pheromone).

The proposed strategy is distributed, reactive and independent of the parameters usually considered in multiple agent systems: environment structure and dimension, number of robots and robots' position. The robots play a sequence of actions (Figure 1) in order to execute the surveillance task, they are: pheromone dispersion, pheromone detection and direction adjustment. That sequence determines an iteration to execute the surveillance task. For all actions of the sequence, the robots keep a constant speed. The robot's angular speed is changed according to the external stimuli detected by the sensors. Each action is described in next sections.

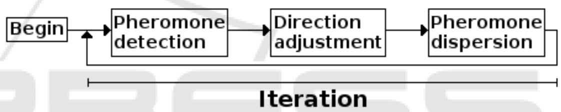


Figure 1: Task diagram for one robot.

2.1 Robot and Sensors Models

The robots are equipped with two types of pheromone sensors. One of them allows the detection of its own pheromone and the other detects only odd pheromone. Both of them has the same physical structure. Consider the index s, $s \in \{own, odd\}$, refers to the pheromone sensors, own and odd, respectively. The sensor field is a sector of a circle C_s defined according to a radius R_s centralized on the robot's frontal part. The sensors covers an area of β_s degrees from the left to β_s degrees from the right of the robot's movement direction, $\beta_s \in [0°, 180°]$ (Figure 2). The total cover area of $2\beta_s$ degrees is divided in identical circular sectors C_{s_i}, each one measuring α_s degrees.

Every iteration, the pheromone sensors detect a set of stimuli from the environment at a specific and parameterizable distance. The detection only occurs at the boundary of the sensors (detection limit).

The robots also possess a proximity sensor. Its model is similar to the pheromone sensors. At each iteration, this sensor detects, in each circular sector, a set of stimuli corresponding to the distance of obstacles. The amount of pheromone accumulated close to obstacles generates not attractive areas for robots.

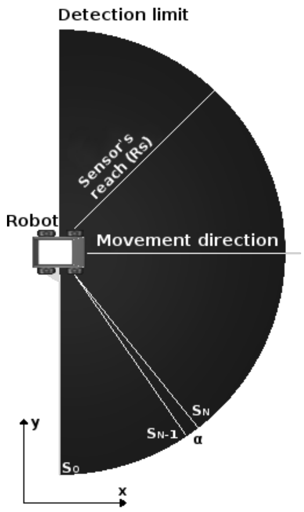


Figure 2: Robot's sensor model.

Then, the pheromone releasing is enough to robots guide over safe trajectories. However, a specific algorithm for obstacle avoidance is triggered at instant that robots face imminent collision situations (for example, if the distance between the obstacle and the robot is too low). That algorithm is activated rarely due to robot's dimensions.

2.2 Direction Adjustment Mechanism

To determine the direction angle, it is proposed a mechanism that combines the information obtained by the pheromone sensors. Consider a set P of circular sectors C_r, in which the $i-$th element of the set corresponds to the quantity of own and odd pheromone of the $i-$th circular sector. From this set, only the sectors with odd pheromone quantity lower than ψ, $\psi > 0$ are selected and inserted to the set Q. From this selection, it is possible to achieve two scenarios:

1) If the quantity of elements in Q is smaller than η, then the robot is located in an area with high concentration of odd pheromone. In this case, the own pheromone becomes attractive (only for this robot), in order to maintain the robot on its own area and not monitor areas visited by the others. Therefore, the content of Q is removed and the elements of P with the highest quantity of own pheromone are inserted in Q until its size is equal to half of P's size. A probabilistic value is attributed to each circular sector C_r in P directly proportional to the quantity of own pheromone deposited on the respective angular interval. Specifically, a probability $P(r)$ attributed to the circular sector C_r is:

$$\overline{P(r)} = \frac{\tau_r}{\sum\limits_{i \in \{r | C_r \in Q\}} (\tau_i)} \tag{1}$$

where τ_r is the quantity of pheromone correspondent to the circular sector C_r.

2) If the quantity of elements in Q is higher than η, it means there is low or none quantity of odd pheromone surrounding the robot. So, these areas have been for a long time without visits (or never have been visited yet). The advance of a robot into areas that are not of its domain is only possible if the own pheromone remains repulsive. Hence, priority is given to the exploration behavior. This way, elements in Q with quantity of own pheromone higher than ψ are removed from the set in such a way that the length of Q will be reduced by up to half. Similarly to the previous scenario, a probabilistic value is attributed to each circular sector, however, inversely proportional to the quantity of own pheromone deposited in the respective angular interval. The probability $P(r)$ is given as:

$$\overline{P(r)} = \frac{1 - \tau_r}{\sum\limits_{i \in \{r | A_r \in Q\}} (1 - \tau_i)} \tag{2}$$

2.3 Pheromone Dispersion and Evaporation

The pheromone is dispersed on a wide frontal area of the robot, corresponding to the area covered by the sensors. The amount of pheromone released in a position changes according to the distance between the position and the agent. Up next, the model of pheromone releasing is described. Consider L_t and Q the coverage area of the sensor in iteration t and the complete space of the environment, respectively, such that $L(t) \subset Q \subset R^2$. The concentration of pheromone $\Delta_q^k(t)$ which the $k-$th robot deposits on the position $q \in Q$ in iteration t is given as:

$$\Delta_q^k(t) = (\tau_{max} - \tau_q(t-1))\Gamma_q^k(t), \text{and} \tag{3}$$

$$\Gamma_q^k(t) = \begin{cases} \delta\, e^{\frac{-(q-q_k)^2}{\lambda^2}}, \text{if } q \in L_t^k \\ 0, \text{otherwise} \end{cases} \tag{4}$$

where q_k is the position of the $k-$th robot; τ_{max} is the maximum limit of saturation of pheromone's concentration; λ is the dispersion rate of pheromone; and $\delta \in (0,1)$.

The pheromone is a volatile substance. Hence, it evaporates at the end of each iteration, i.e, when all robots complete a cycle of tasks. The amount of evaporated pheromone, given by the equation (5) depends on the specific rate, a parameterizable constant and the amount of pheromone on the area at the given instant.

$$\varepsilon_q(t) = \phi\tau_q(t) \quad (5)$$

where ε, $0 \leq \varepsilon \leq 1$, is the evaporation rate and $\tau_q(t)$ is the total amount of pheromone on the position q in the instant t.

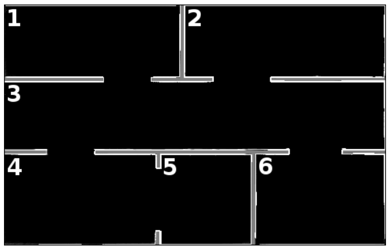
3 EXPERIMENTAL RESULTS

This section presents the experiments to validate the proposed strategy (PSS). The results are analyzed and compared with a coordination strategy already known with results proved in previous researches for the exploration task and surveillance of unknown environments, called in this paper as traditional strategy (Calvo et al., 2015; Calvo et al., 2012). The performance of the PSS strategy is satisfactory if it is similar or superior than the performance of the traditional strategy. The surveillance task is executed if the entire of the environment are sensed.

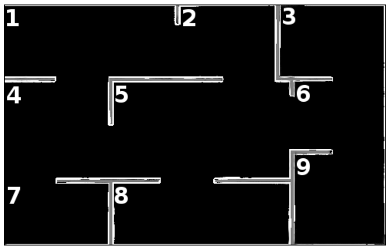
The platform *Morse Simulator* is used to execute the experiments. The model adopted for the robots is the ATRV, equipped with the sensor SICK LMS 500. For both strategies, was adopted the following parameters: ($s \in \{own, odd\}$); $R_s = 10m$; $\beta_s = 90°$; $\gamma = 0.4$; robots' linear speed = $0.5m/s$; $S = 360$; $\phi = 0.01$; $\tau_q(0) = 0.5$ (quantity of pheromone at iteration $t = 0$ for each $q \in Q$). These parameters were defined according to the numerous tests executed previously.

The experiments are performed in environments with dimensions of 80×50m (Figure 3). The environments are divided in connected regions called *rooms*. Each one of them are divided in small squared areas called *cells*. The cells are portions of the environment used to check if the entire of the environment is sensed. At instant when robots visit all cells at least once, then it is said that a cycle of surveillance was completed. After that, a new cycle os surveillance is started. Two criteria of evaluation are adopted to the experiments: number of cycles of surveillance completed through the simulation and the average of iterations between two consecutive completed cycles. Each simulation is executed 30 times with 2000 iterations.

The PSS strategy is validated by means of the analysis of its performance when compared to the traditional strategy. The maps correspond to the simulation whose performance is closer to the average performance obtained in the simulations. Next, is presented the performance of each strategy of coordination.



(a)



(b)

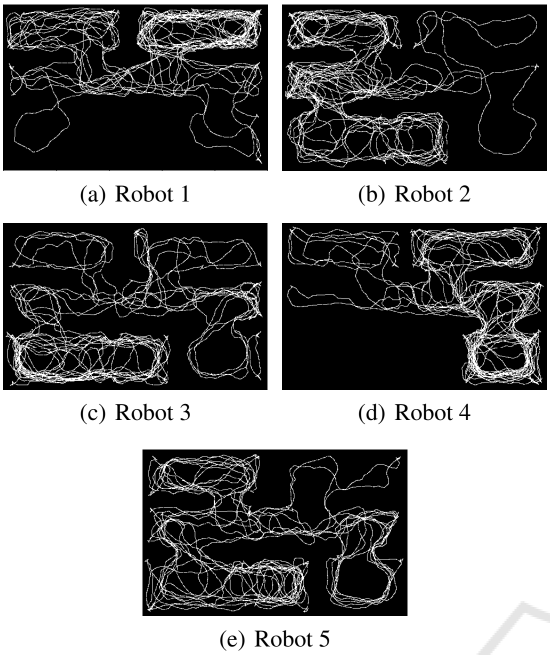
Figure 3: Environment models: (a) #1; (b) #2.

3.1 Traditional Strategy

In the traditional strategy, the direction adjustment occurs differently from the PSS strategy. Here, the robots do not distinguish the types of pheromones. Only one kind of pheromone is detected, and it has only the repulsive property. The direction adjustment is also based on a probabilistic model, but the best circular sectors to be chosen are those which have low pheromone. Others sectors are chosen randomly to favor the exploratory behavior in the environment. In this strategy, the robots tend to monitor areas with low or none pheromone quantity, regardless of the agent that deposited it.

Considering the environment #1 (Figure 3(a)), the traditional strategy is performed, using five robots, all of them starting on the room of number 1. In 30 simulations, the robots completed an average of 20.5 cycles (standard deviation of 1.1670), with an average of 95.28 iterations per cycle (standard deviation of 5.2373). The Figures 4 and 5 show the trajectory and the average of pheromone deposited on the environment for each robot, respectively.

Note that, in Figure 4, the robots traveled throughout the environment, each one occupying, practically, all rooms on a same simulation. The Figure 5 shows the average of pheromone deposited by the robots in one simulation. This information indicates the most visited areas by the robots and that the robots were too close to each other. The occurrence of this situation leads to the waste of resources like sensor and traveled path. The concentration of close robots also causes the increase of time in which a room re-

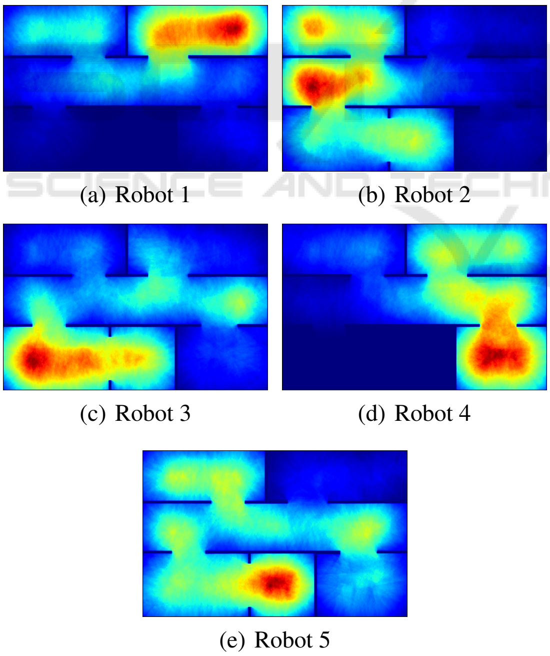


(a) Robot 1 (b) Robot 2

(c) Robot 3 (d) Robot 4

(e) Robot 5

Figure 4: Trajectory of the robots on the environment #1 using the traditional strategy.



(a) Robot 1 (b) Robot 2

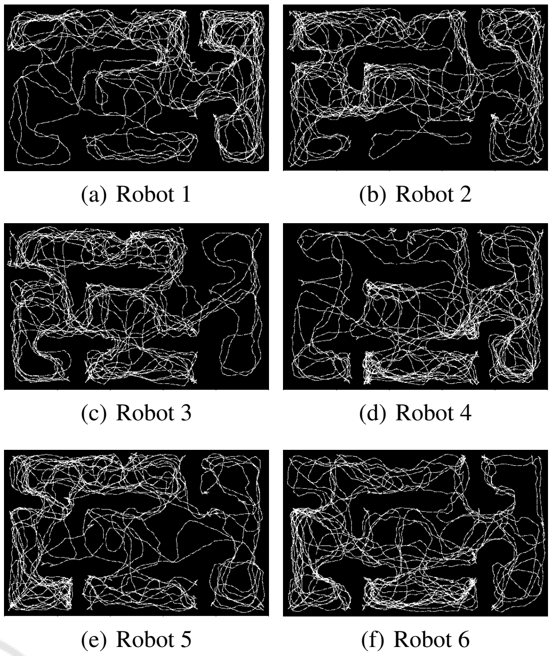
(c) Robot 3 (d) Robot 4

(e) Robot 5

Figure 5: Average of pheromone dispersion on the environment #1 using the traditional strategy.

mains unvisited.

For the environment #2 (Figure 3(b)), six robots are employed. All of them started on the room of number 1. The average amount of surveillance cycles completed was of 26.16 (standard deviation of 1.7827), with an average of 74.81 iterations per cycle (standard deviation of 4.6290). Similarly to the previous experiment, the robots are dispersed throughout the environment, alternating the visits among the rooms. The Figure 6 shows that the robots occupied all rooms. According to the Figure 7, it can be

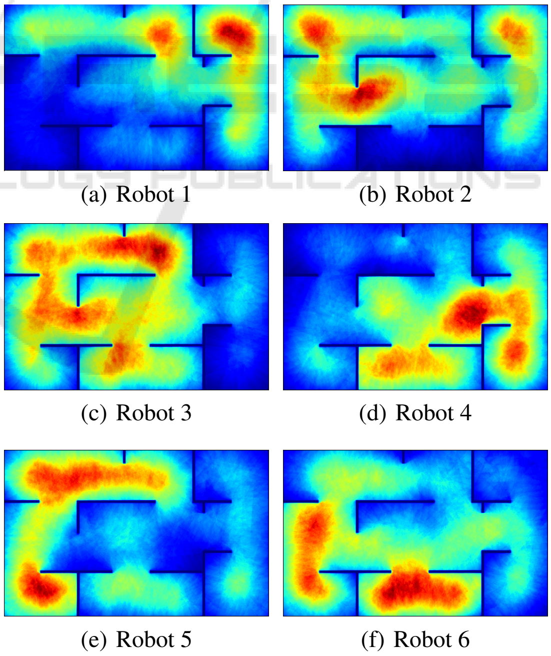


(a) Robot 1 (b) Robot 2

(c) Robot 3 (d) Robot 4

(e) Robot 5 (f) Robot 6

Figure 6: Trajectory of the robots on the environment #2 using the traditional strategy.



(a) Robot 1 (b) Robot 2

(c) Robot 3 (d) Robot 4

(e) Robot 5 (f) Robot 6

Figure 7: Average of pheromone dispersion on the environment #2 using the traditional strategy.

seen that many robots remained on the same rooms, in most part of the simulation, indicating proximity with each other. This means that another rooms of the scene remained without visits for a long period.

3.2 Partitioned Strategy

The robots' behavior on the partitioned strategy consists of the dispersion throughout the environment in a way that the monitored region by a robot do not get occupied by any other robot. After a period in which each robot is on a region, it is said that the strategy stabilized itself. At this instant, the robots defined their own partition on the environment. The following experiments show this behavior.

For the environment #1, five robots are used, starting on the room number 1. The number of completed surveillance cycles is, on average, 26.36 (standard deviation of 2.5795), with an average of 75.23 iterations per cycle (standard deviation of 7.5414). Compared to the traditional strategy, the partitioned strategy increased about 28.59% the number of average completed cycles. This is due to the better surveillance task distribution among the robots.

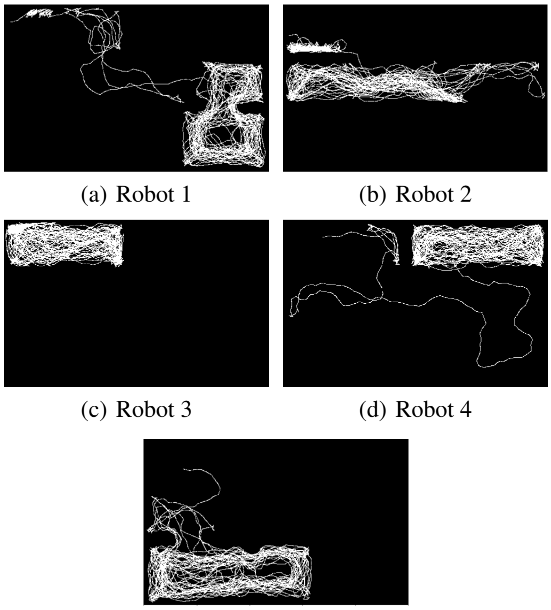
The Figures 8 and 9 show the environment's partition, where each robot remains on its own area individually.

On the environment #2, for six robots starting on room number 1, the average of completed cycles was 31.83 (standard deviation of 3.0522), with an average of 62.59 (standard deviation of 5.7205) iterations per cycle, an increase of 21.67% of number of completed cycles. Figures 10 and 11 show that, even in a different environment , the strategy's behavior still keeps the map partitioned among the agents.

The Tables 1 and 2 summarize the results for both experiments. The S.D. column stands for standard deviation of its previous column.

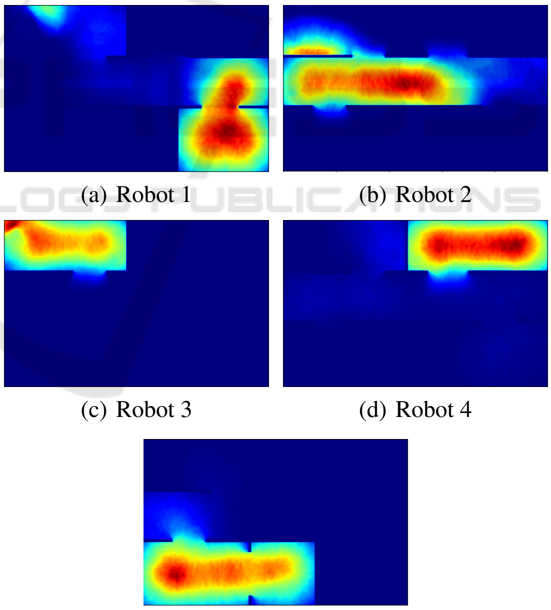
The main reason for the better performance of the PSS strategy is highly tied to the partition of the environment whose partitions are occupied by only one robot. The presence of odd pheromone avoid a robot move to occupied partition. That behavior induces a robot stay in areas with its own pheromone, i.e, areas where that the robot visited recently.

If each robot patrols its own partition, there will not redundancy of covered areas, improving the performance of the surveillance task. Therefore, the execution of the task is distributive and more effective than the strategy where the robots do not able to split virtually the environment in small partitions.



(a) Robot 1 (b) Robot 2 (c) Robot 3 (d) Robot 4 (e) Robot 5

Figure 8: Trajectory of the robots on the environment #1 using the partitioned strategy.



(a) Robot 1 (b) Robot 2 (c) Robot 3 (d) Robot 4 (e) Robot 5

Figure 9: Average of pheromone dispersion on the environment #1 using the partitioned strategy.

4 CONCLUSIONS

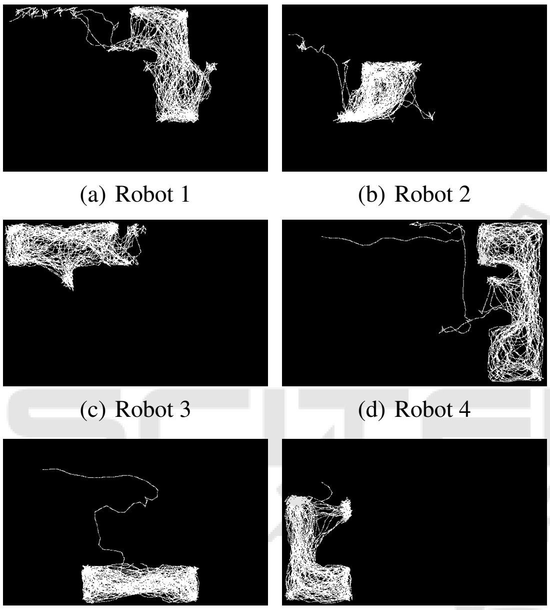
The PSS strategy presented a higher performance than the traditional strategy. The fundamental feature of this strategy consists on the ability to partition the

Table 1: Results of the experiments on environment. #1.

Strategy	Average cycles	S.D.	Average iterations per cycle	S.D.
Traditional	20,5	1,1670	95,28	5,2373
Partitioned	26,36	2,5795	75,23	7,5414
Increase	28,59%	121,04%	-21.04%	43,99%

Table 2: Results of the experiments on environment. #2.

Strategy	Average cycles	S.D.	Average iterations per cycle	S.D.
Traditional	26.16	1,7827	74.81	4.6290
Partitioned	31.83	3.0522	62.59	5.7205
Increase	21,67%	71,21%	-16.33%	23,58%

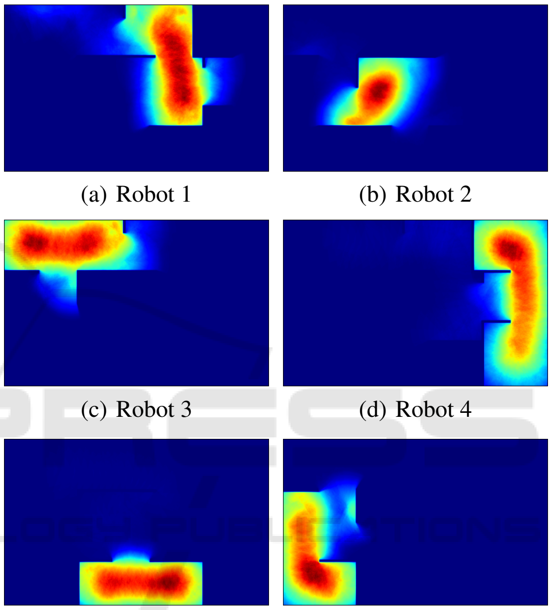


(a) Robot 1 (b) Robot 2

(c) Robot 3 (d) Robot 4

(e) Robot 5 (f) Robot 5

Figure 10: Trajectory of the robots on the environment #1 using the partitioned strategy.



(a) Robot 1 (b) Robot 2

(c) Robot 3 (d) Robot 4

(e) Robot 5 (f) Robot 5

Figure 11: Average of pheromone dispersion on the environment #1 using the partitioned strategy.

scene autonomously into smaller sectors, in which just one robot remains on the sector, performing the surveillance task. The fact that a robot does not invade other's areas avoids the redundant monitoring of the same region, distributing the surveillance equally on the environment.

As future works, it is intended to verify the influence of the pheromone evaporation and dispersion rates on the number of robots and the dimensions of the environment. Investigate the behavior of the agents with scenes without obstacles and develop a strategy for this scenario that can simulate, for example, a distribution task of a mobile phone operator's antennas. Also it is intended to make feasible the PSS strategy on real robots, along with mapping and location algorithms needed for the surveillance task.

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