Inverse ACO Applied for Exploration and Surveillance in Unknown Environments

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*—This paper focuses on a distributed strategy proposed to coordinate a multiple robot system applied to exploration and surveillance tasks. The strategy is based on the artificial ant system theory. According to it robots are guided to unexplored or not recently explored regions. The main features of the strategy are, among others: low computation cost; and independence of the number of robots. Results from preceding investigations confirm the strategy is able to emerge a cooperative robot behavior, that is, the exploration and surveillance tasks are synergistically executed. This paper concerns specifically the robustness of the coordination strategy regarding to the environment structure. Two metrics are adopted for evaluation: needed time to conclude the exploration task, and time between two consecutive senses on a same region. Simulation results show that the coordination strategy is able to establish effective trajectories, that is, robots are guided to explore the environment and to sense repeatedly and completely the environment.**

***Keywords*-multiple robot systems; surveillance task; ant colony systems; environment exploration; swarm systems; mobile robots**

I. INTRODUCTION

The more sophisticated is the robotic field technology the higher is the possibility of multiple agent systems to become usual. This expectation associated with the potential advantages of using multiple agents over a single one captivates the attention of the scientific community. Nowadays, the literature provides many articles that focus on multiple robot systems applied to basic tasks, such as: exploration, covering, and surveillance [1], [2].

The enormous potential associated with the multiple agent systems is exploited only if the respective coordination strategies are efficient. Whatever the task is considered, they have to satisfy some basic requirements, such as: small redundancy of agent effort; and strong cooperative agent behavior [3]. Other requirements come from the task the robots have to accomplish. Considering all things together, it is plausible the design of coordination strategies for multiple agent systems is a challenge problem in robotics [4].

The strategy described in [5] is able to guide robots applied to construct a common map cooperatively as they explore the environment. The authors introduce the notion of a frontier, which is a boundary between the explored and unexplored areas. As the robots move, new boundaries are detected and frontiers are grouped in regions. Then, robots navigate toward the centroid of the closest region, while sharing maps. The strategy, centralized and based on the A* algorithm, receives information from every robot and defines the next steering direction of each robot..

Several applications of multiple agents are designed to accomplish security and surveillance tasks [6]. Coordination strategies based solely on mathematical formulation are very parameter dependent and suffer critical degradation due to agent failure [7]. Bio-inspired and evolutionary theories provide fundamentals to design alternative strategies [8].

The technique in [9] focuses on intelligent decision making for security. During the security mission, robots engage in four behaviors: patrol, inspect, chase intruder and guard. A fuzzy logic-based method is used for decision making that establishes qualitative relationships, in terms meaningful to human information, between different possible input types and efficient outputs.

The surveillance system described in [10] is to detect changes in environment comparing color histograms between current images and those images previously taken. Unfortunately the environment is totally static.

Considering the surveillance problem, the coordination strategy named Inverse Ant System-Based Surveillance System (IAS-SS) is once more investigated. It is designed according to a modified version of the ant algorithm presented in [11]. Results from preceding investigations confirm that the strategy is able to emerge a cooperative robot behavior, that is, the exploration and surveillance tasks are synergistically executed. This paper concerns specifically the robustness of the coordination strategy regarding to the environment structure. Different environment structures are considered, all of them designed from a rectangular space divided in 10 small spaces. Passage ways that connect spaces may be partially or totally blocked using walls. Following this procedure, 10 environment structures, each of which associated with a particular degree of complexity, are considered to evaluate the performance of the coordination strategy. Two metrics are adopted for evaluation: needed time to conclude the exploration task, and time between two consecutive senses on a same region. Simulation results show that the coordination strategy is able establish effective trajectories, that is, robots are guided to explore the environment and to sense repeatedly and completely the environment.

The remainder of the paper is organized such as follows. Section II provides fundamentals of the artificial ant system theory. The description of the multiple robot system for exploration and surveillance tasks and the coordination strategy IAS-SS are the focuses of the Section IV. Section V shows simulation results obtained from a set of experiments. The main contributions and relevant aspects of the 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 [12].

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 stigmergy). 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. Stigmergy mechanism is considered one of the factors that decisively contribute to amplify the capabilities of a single ant. Ant colonies use the stigmergy mechanism to coordinate their activities in a distributed way [13].

Artificial ant systems are the artificial counterparts of the biological ant colonies, designed to solve complex problems, among others: optimization combinatorial problems [11]. Analogously artificial ants (e.g., robots) are able to use the stigmergic communication. Pheromone trail provides a type of distributed information that artificial agents may use to take decisions or modify to express previous experiences [14]. A distributed coordination behavior emerges from this capability, providing solutions to problems associated with exploration in hyperspace.

III. Definitions and Preliminary Concepts

The collaborative behavior of robots is based on the repulsion instead of the attraction to pheromone. In order to mark a specific region as visited, a robot leaves pheromone on its position along the navigation. According to adopted pheromone's repulsion characteristic, the robot's reaction consists in avoiding paths already covered. Analogous to real ants colony, the pheromone deposited by robots are open to evaporation phenomena. This provokes a gradual reduction of amount of pheromone of the region. Therefore, the robots are in constant searching regions with low amount of the pheromone. As consequence of evaporation, the robots realize exploration and surveillance behaviors.

Differently from works related, the surveillance term referred in this paper consists in the coverage of a determined environment in a continuous way. This requires that the robots to walk in the environment continuously and to visit many times parts of the environment. So, they are spread out in order to minimize the execution time and have the optimal coverage. The great challenge for solving this problem is in the coordination of the robots and in the definition of their trajectories.

The multiple robot system is composed by a group of $k \in \mathbb{N}^*$ identical robots vehicles, where each robot has the capacity for measuring a sensory function from the environment with sensor range radius R. The sensory function indicates the relative importance of different areas in the environment. It can represent the quantity that is detected by the robot's sensor directly, such as the temperature or lightness of the environment. More specifically, in our case, the sensory function measures the quantity of the detected concentration of a chemical substance. The sensory function is defined as

$$f : A \subset \mathbb{R} \quad \longmapsto \quad \mathbb{R} \tag{1}$$

where A is the set of sensor signals received by robot at each instant.

We are assuming that robots r_i, $i = 1, \ldots, k$ move in planar workspace $Q \subset \mathbb{R}^2$ and that an arbitrary point in Q is denoted by q. It is also assumed that the robot's position in the environment is known previously. Let L_t^i be the covered area by the sensor of $r_i th$ robot at instant t. A point $q \in Q$ is visited by $r_i th$ robot at instant t, if $q \in L_t^i$ and $r_i(t^q) = 1$. Let us also to consider the following definitions. At the instant when the environment is entirely covered, it is said that a Surveillance Epoch (SE) is completed. In each SE, all points $q \in Q$ are visited at least once. The period of time needed to cover the whole environment (all points) and to conclude a SE is denoted by *Surveillance Interval (SI)*. So, we can define that an optimal coverage of the environment for surveillance task is achieved by minimizing the period of time SI.

Then, the main aim is to reduce the period which a point q is non visited. Let us to consider t_1^q and t_s^q be the instants when any robot visits the point q, such that, $t_1^q < t_2^q$ and that $q \in Q$ is non visited at any instant t within interval (t_1^q, t_2^q). Thus, the shortest time interval between any two consecutive visits of any point q is given by:

$$min \sum_{q \in Q} (t_2^q - t_1^q)$$

subject to:

$$r_i(t^q) = 0, \;\; \forall i = 1, \ldots, k \;\text{ and }\; \forall t^q, t_1^q < t^q < t_2^q;$$

$$r_i(t_1^q) = 1, \ \forall i = 1, , \ldots, k;$$

$$r_i(t_2^q) = 1, \ \forall i = 1, \ldots, k$$

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

While the robots navigate, they deposit a specific substance, the pheromone (the analogue of the pheromone in biological ant systems), into the environment. At each time each robot receives stimuli from the pheromone and adjusts its navigation direction. This is the only one decision that a robot takes. In fact, the robot navigation system considers a set of stimuli detected at different angles and same distance. The lesser is the detected amount of the substance the greater is the probability that the robot takes the navigation direction equal to the angle where this amount of substance is.

The logic of the decision in the IAS-SS is the opposite of that adopted in the traditional ant system theory. The logic adopted there generates a positive feedback, that is, the greater the amount the substance the greater is the probability of the agent to follow the respective direction.

The block diagram in Figure 1 represents the sequence of main actions that an agent system performs at each iteration.

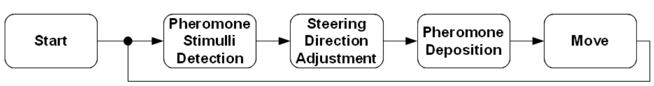


Figure 1. Functional Diagram Block for a single agent.

It is important to mention that the robots exhibit the obstacle avoidance behavior, but there is no specific embedded navigation mechanism for that. In fact this navigation skill emerges from the synergy among the artificial agents as a natural consequence of how the pheromone is released on the environment and the effects the pheromone stimuli generate.

A detailed description of the IAS-SS system is given below. Consider a group of N robots $k, k = 1, \ldots, N$. Every robot k performs two basic operations: steering direction adjustment and pheromone deposition.

A. Steering Direction Adjustment

Two strategies to determine the steering direction angle are adopted in [15]. The first, Stochastic Sampling (SS), considers all pheromone stimuli that the sensor detects at the border of its range (Figure 2). The second, Best Ranked Stochastic Sampling (BRSS), determines the adjusting of steering angle based on only those stimuli associated with the least amount of pheromone. However, Stochastic Sampling mechanism showed to be efficient for large areas where the amount of pheromone deposited is similar on every point due to the stochastic nature of the strategy. Because BRSS strategy maximizes the explored area in reduced period of time, only it is considered here.

The model of the sensor adopted is such that it detects pheromone stimuli at a specific distance R, from -90 degrees to 90 degrees, corresponding to the average of the amount of pheromone deposited in an angle interval. The total range of 180 degrees is divided in identical angle intervals, such that the sensor detects stimuli corresponding to different angles A_s, s = 1, ..., S.

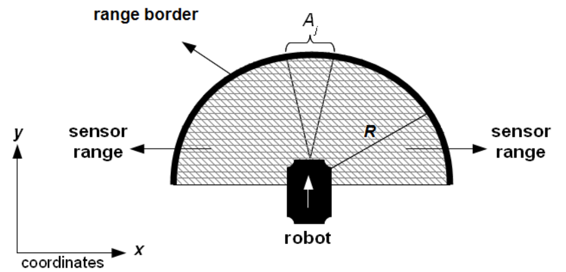


Figure 2. Robot and sensor models

1) Best Ranked Stochastic Sampling: Two subsets of angle intervals S is considered to define the steering direction. The first, subset U the angle intervals are those that the amount of pheromone is very low. Specifically, the strategy sorts the intervals according to the respective amount of the pheromone. Then only those angles A_s associated with the least amount of pheromone (best ranked intervals) are considered to define the steering direction. The second subset V consists of elements chosen randomly, according to a uniform distribution, from the angles A_s that are not in the first subset.

A probability value is assigned to each discrete angle in both of the subsets U and V. The probability assigned to the angle A_s is inversely proportional to the amount of pheromone deposited in the respective angle interval, that is, the lower is the amount of pheromone detected, the higher is the probability associated with the angle. Specifically, the probability $P(s)$ assigned to the angle A_s is:

$$P(s) = \frac{1}{\tau_s / \sum_{i \in \{U,V\}} \tau_i} \tag{2}$$

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

The adjusting of steering direction is determined according to a discrete random variable a defined through the probability $P(s)$, assuming values in the set $A_s, s = 1, ..., S$.

According to this strategy, robots tend to move to directions where there is low amount of pheromone. The general behavior observed is that the robots move to unexplored areas or areas scarcely visited by robots during some period of time. The adjusting of steering direction is given by:

$$\Theta_k(t) = \Theta_k(t-1) + \gamma A(s^*) \tag{3}$$

where $\Theta_k(t)$ is the steering of movement of robot k at instant t, $\gamma \in [0, 1]$ is the constant coefficient for smoothing of steering direction adjusting and $A(s^*)$ is the selected direction by probability of equation 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 [11]. Differently, the artificial agents in the IAS-SS spread pheromone on a wide area in front of their respective positions, corresponding to sensor range area.

Once the agent determines the steering direction, but before it moves, it spreads pheromone. The amount of pheromone deposited on the ground decreases as the distance from the robot increases. The model for the pheromone releasing is such as follows. Consider that L_t and Q are the sensor range area at iteration t and the entire environment space, respectively, such that $L_t \subset Q \subset \mathbb{R}^2$. Then, the amount of pheromone $\Delta_X^k(t)$, that the kth robot deposited on the position X at iteration t is:

$$\Delta_X^k = \begin{cases} e^{\frac{-(X-X_k)^2}{\sigma^2}}, \text{if } X \in L_t \\ 0, \text{otherwise} \end{cases} \tag{4}$$

where X_k is the position of the kth robot and σ is the Gaussian dispersion.

Multiple robots deposit pheromone in the environment at same time, then the total amount of pheromone deposited on the position X 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 $\Phi_X(t)$ at position X and time t is modeled such as follow:

$$\Phi_X(t) = (1-\rho)\tau_X(t) \tag{5}$$

where ρ is the evaporation rate and $\tau_X(t)$ is the total amount of pheromone on the position X at iteration t.

Therefore, the total amount of pheromone $\tau_X(t)$ at X and at time t is (Equation 6):

$$\tau_X(t) = \Phi(t-1) + \sum_{k=1}^{K} \Delta_{x,y}^k \tag{6}$$

V. Experimental Results

Experiment simulations are developed to evaluate preliminarily the bioinspired coordination strategy IAS-SS. The strategy is considered to generate the dynamics of multiple robot systems applied to exploration and surveillance tasks.

Experiments are carried out in Player/Stage platform that models various robots and sensors simulating simultaneously their exact dynamics. Although this platform includes navigation mechanism for obstacle avoidance, this behavior, in IAS-SS system, emerges only from consequence of repulsive nature of pheromone. The robot model used is Pioneer 2DX equipped with laser range-finder SICK LMS 200.

The exploration task is executed if the environment is completely covered. Moreover, the faster the system completes the task, the better is the performance; 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, it is important that the system conclude 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 the performance.

The system parameters used in the experiments are: $\sigma = 0.4R$ (pheromone releasing rate); $\rho = 10^{-4}$ (evaporation rate); $\tau_X(0) = 0.5$ (the amount of pheromone at iteration $t = 0$); $R = 8.00$ meters (radius of the semicircle where the pheromone is deposited and provided by laser range finder); $\gamma = 0.5$ (coefficient for smoothing of steering direction adjusting); Robot speed: 0.5 meter per second; $S = 360$ (number of angle intervals); Number of elements of subsets U and V correspond to 30% and 10% of size of S set, respectively; Maximum number of iterations of simulations: 1000. The values assigned to parameters σ and ρ are defined through analysis of performance of IAS-SS in [15].

The steering direction strategy adopted for all experiments is BRSS (see Section IV-A1) due to its more efficient performance than other strategies described in [15]. According to randomness characteristic of this strategy, all experiments are executed 3 times. 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.

The environments where the IAS-SS system carries out the tasks are divided in connected small regions called here rooms. The used division model of environments in following experiments is illustrated in Figure 3(a). The environments are designed from the division model according to a complexity level. This 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 Figure 3(b). The more path options to reach a specific region are available, the complexity level of environment is higher. For environments of Figures 3(c) and 3(d), the graph structure is the same of the graph of Figure 3(b), hence, the complexity is low. As obstacles are inserted into environments blocking the passage among rooms, the respective edges of graph are removed and, thus, the complexity is higher.

For analysis, the rooms are numbered (Figure 3(a)). 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 defined in equation 1. Hence, the scenario considered here is an instance of the problem formulated.

Since there are ten rooms, four robots are considered for

 ISBN: 978-1-61208-155-7

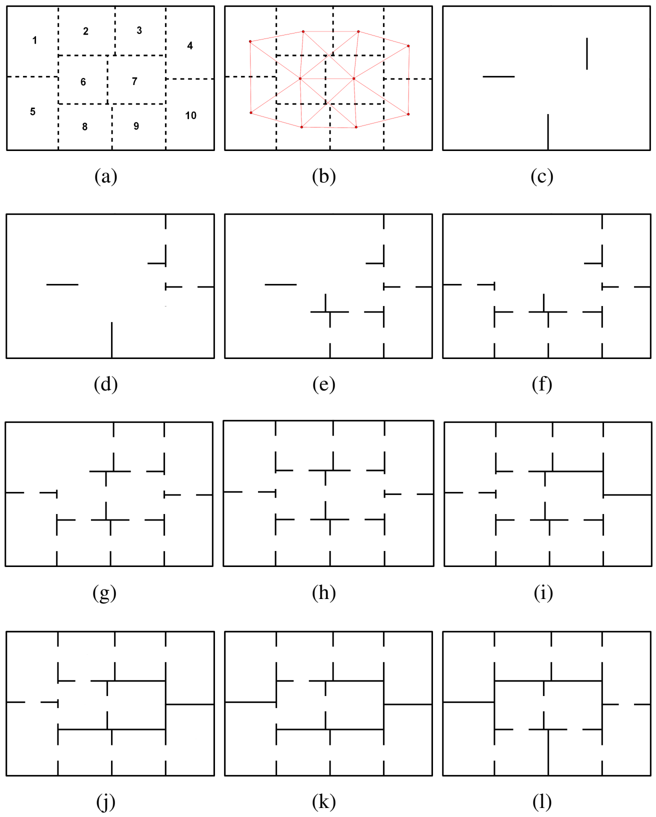


Figure 3. Environment models: (a) environment divided in rooms; (b) connection graph among rooms; (c)-(l) environment from $\#1$ to $\#10$.

Table I
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 ± 0.73	114.17 ± 23.82
$\#9$	7.51 ± 1.32	119.49 ± 3.88
$\#10$	7.33 ± 1.52	115.23 ± 24.9

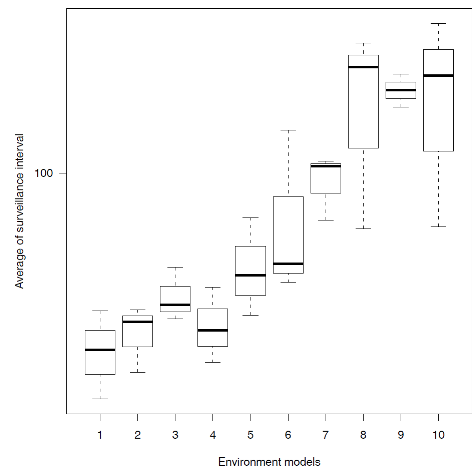


Figure 4. Boxplots of distribution of the average of surveillance intervals for different degree of complexity of environment.

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 increases 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 I. The average of number of SE decreases and the average of SI presents a strong increasing 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 4. It shows the boxplots of the distribution of the performance.

Additional information about the behavior of the system can be gathered observing the Figure 5. Data used to plot the graphic are from the trial with the median number of SI for simulation of environment $\#5$. Four graphics are presented, each of which registering the behavior (room changing) of one of the robots. Each vertical line indicates the SE, that is, the iteration when the IAS-SS senses the entire environment (the robots visit cooperatively all the 10 rooms), considering that a new sense task is started after the system concludes the earlier one.

The self-adapt trait of the system is visualized through the trajectories of robots in Figure 6. Due to limited space, only the obtained trajectories from simulation of environments $\#1$, $\#5$ and $\#10$ are showed in order to contrast the high difference of complexity level among them. It can be 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 $\#5$, 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.

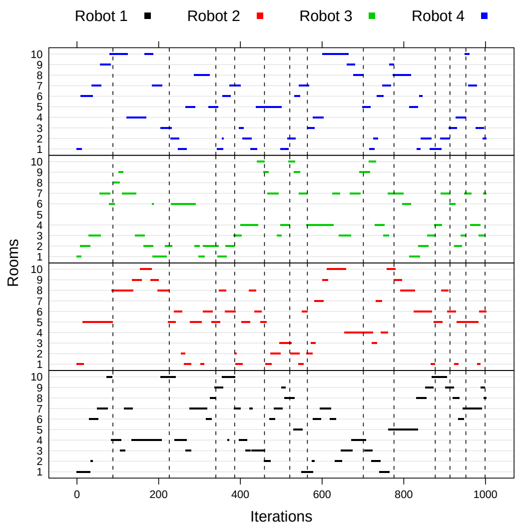
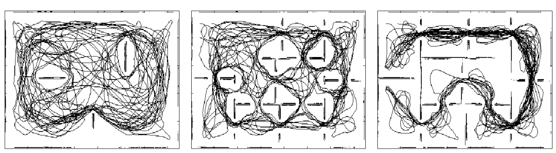


Figure 5. IAS-SS performance according to environment #5.



(a) (b) (c)

Figure 6. Trajectories of robots during exploration and surveillance tasks: environments (a) #1; (b) #5; (c) #10.

VI. Conclusions and Future Works

This work described a new bioinspired distributed coordination strategy, named IAS-SS, for multiple agent systems applied to exploration and surveillance tasks. The strategy is based on a swarm theory, specifically the ant system theory. The IAS-SS strategy defines steering directions that guide preferably the agents to where the amount of pheromone is lesser. The strategy is not dependent on the knowledge of the environment structure and changes the system dynamics in order to reach a good performance.

As future works some parameters of the IAS-SS system will be considered for analysis, e.g., the pheromone releasing mechanism. Moreover, a localization method will be integrated to IAS-SS system in order to deploy it in real robots. In this case, a chemical sensor will be attached to the front of robot. Similarly, a device to disperse the chemical will be deployed. A more simple way is to consider only distance sensor and set the cells of built map to indicate that there is amount of pheromone at respective position. In addition, more complex surveillance tasks, e.g., those that a strange agent invades the environment, will be investigated.

Acknowledgment

The authors would like to thank FAPESP and CNPq for their support.

References

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

[2] 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.

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

[4] 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.

[5] B. Yamauchi. "A frontier-based approach for autonomous exploration". Proc. of the 1997 IEEE Int. Symp. on Comp. Int. in Rob. and Aut., pp. 146-151, 1997.

[6] H. R. Everett. "A brief history of robotics in physical security". Space and Naval Warfare Systems Center, San Diego, Robotics Publications, 2010.

[7] R. A. Freeman, P. Yang and K. M. Lynch, "Distributed estimation and control of swarm formation statistics", *American Control Conference.*, 7, 2006.

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

[9] M. Lee, M. Tarokh and M. Cross. "Fuzzy logic decision making for multi-robot security systems". Artif. Intell. Rev. vol. 34, issue 2., pp. 177-194. Kluwer Academic Publishers. Norwell, MA, USA, 2010.

[10] M. Castelnovi, P. Musso, A. Sgorbissa and R. Zaccaria. "Surveillance robotics: analyzing scenes by colors analysis and clustering," Proc. of 2003 IEEE Int. Symp. on Comp. Int. in Robotics and Automation. vol.1, no., pp. 229- 234 vol.1, 16-20 July 2003

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

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

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

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

[15] 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". Proc. of the IEEE IJCNN. San Jose, USA, 2011.