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Integration of virtual pheromones for mapping/exploration of environments by using multiple robots

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***Abstract*— The multiple robot coordination strategies have several advantages when compared to strategies based on a single robot, in terms of flexibility, gain of information and reduction of map building time. In this paper, a local pheromone map integration method is proposed based on the inter-robot observations, considering a method for the environment exploration named the Inverse Ant System-Based Surveillance System strategy (IAS-SS). Simulation results show that the map integration method is efficient, the trials are performed considering a variable number of robots in an indoor environment. Results obtained from several experiments confirm that the integration process is effective and suitable to execute the control of the access to pheromones in a virtual way.**

I. INTRODUCTION

In biological systems, a remarkable phenomena is the superior performance of a collective of agents over simple one's ability. 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 [1], [2], [3]. Some of the main reasons that justify this choice, among others, are: great dimension of the task and reduced resources (e.g.: velocity, strength and energy) provided for a single robot, necessity to adaptation to spatial or temporal variation of service demand and robustness.

In robotics field, an important aspect of multiple agents systems is the coordination that allows the system accomplishes efficiently general tasks, such as: exploration, coverage, mapping, surveillance, among others. Coordination strategies are designed to provided multiple agent systems with a set of characteristics, e.g.: decentralized coordination, small redundancy of agent efforts and strong cooperative behavior.

The strong expectation associated to these characteristics captivates the attention of the scientific community. Different aspects are investigated in multiple agent systems, such as: agent communication and information merging [4], [5], [6]. Moreover, designers devote effort to concept coordination strategies that are dependent on the least number of parameters as possible. A trickly parameter is the number of agents. Another requirement that may depreciate the strategy is the total knowledge of the environment.

Coordination strategies based solely on mathematical formulation and agent and environment models are very parameter dependent and suffer critical degradation due to agent failure [7], [8]. Bio-inspired and evolutionary theories provide fundamentals to design alternative strategies [9]. The characteristics of biological systems has been received attention of researchers for designing artificial systems. 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 [10].

According to a technique described in [11] 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 robots efforts. Another method based on distributed multi-robot coordination algorithm to accomplish an area exploration task is proposed in [12], given that the communication range of each robot is limited. However, the mapping method presented is based on the knowledgement of the initial relative positions of the robots.

Methods based on stimergy fields for cooperation have been recently employed in the context of robotic exploration [13], [14], [15]. 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 relevant alternative for the coordination problem is the strategy proposed by Calvo et al. [16], [17], [18], [19], named Inverse Ant System-Based Surveillance System (IAS-SS). The IAS-SS strategy is not dependent on the knowledge of the environment structure and it is robust in regard to the number of robots. It is designed according to a modified version of the ant algorithm [20]. In this strategy, the agents were able to indirect communication as the biological agents are, but their reaction to the pheromone is distinct, stering directions are defined to guide preferably the robot to where there is low quantity of pheromone. Thus, the robots tend to keep spread from each other and move to unexplored and not recently explored regions.

However there is a important aspect that must be analyzed when the IAS-SS strategy is applied in real environments using real robots. Specifically, the main question is how the pheromone, described in the exploration and surveillance strategy, will be released by real robots. Experiments per-

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formed in [16], [17], [18], [19] consider a mechanism for accessing of data based on a pheromone global map. This data structure controls all access to pheromone information, but it is not applicable to real environments, since the robots do not have a central processing unit.

Initially the more evident option is the application of pheromones in real environments using physical devices [24], [25], [26]. Although the concretization of the pheromone question can be realized with physical devices, using the main ideas prosed by Ferri et al. [26], the use of such concept can be adverse, according to the environment in which the robots are, for example, a office.

A solution for this problem is to use an approach based on virtual pheromone [21], [22], [23]. In the present work, a local pheromone map integration method is proposed based on inter-robot observations, considering the IAS-SS strategy as method of environment exploration and using the virtual pheromone concept.

The proposed integration method is an extension of the approach elucidated in [27], where the mobile robots spread out across certain area and share information through an ad hoc Wireless network. The multiple robot system is a mobile sensor network, which consists of a variety of sensors on a collection of mobile robots. The objective for the cooperation of multiple robots is to cover certain area using the onboard sensors. According to Tan et al. [27], each robot is responsible for monitoring certain part Ω of the entire environment. The local coordinate system for each robot may be different and time variant.

The method proposed here integrates pheromone maps using the information sharing model proposed by [27], the local map joining is defined by transformation matrices, represented by the distance between two robots and their relative positions.

The remainder of the paper is organized such as follows. In Section 2, it is provided a description of the multiple robot strategy for exploration and surveillance tasks IAS-SS. The pheromone map integration method based on inter-robot observations proposed here is the focus of Section 3. In Section 4, it is shown simulation results obtained from a set of experiments. The main contributions of the paper as well as expectations for the future works are highlighted in Section 5.

II. INVERSE ANT SYSTEM-BASED SURVEILLANCE SYSTEM (IAS-SS)

In IAS-SS, during the navigation by the environment, the robots deposit a specific substance, denominated here as pheromone (the analogue of the pheromone in biological systems), on the environment. At each time, each robot receives stimuli from the pheromone and adjusts its navigation direction. This is the only action that robot takes. 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 is. The logic of the decision in IAS-SS is the opposite of that adopted in the traditional ant system theory.

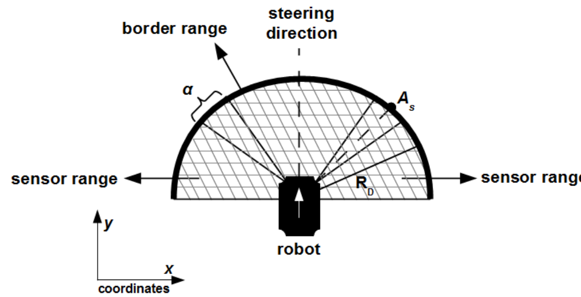


Fig. 1. Robot and sensor model

A description of IAS-SS strategy is given to follow. Consider a group of N robots k, k = 1, …, N. Every robot k performs two operations: steering direction adjustment and pheromone deposition. The model of the sensor is such that it detects pheromone stimuli at a specific distance R_D, as shown in Fig. 1, 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, such that: $(2S+1)\alpha = 180$ and $A_s = s\alpha$, where $s \in [-S, S]$ and $s \in \mathbb{N}$.

Two subsets of angle intervals S are considered to define the steering direction. The first, subset U, the angle intervals are those that the amount of pheromone is very low. The second, subset V, consists of elements chosen randomly, according to an uniform distribution, from the angles A_s that are not in the first subset. The subset V is built for ensuring the representativeness of the angle intervals.

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 $s, z = -S, \ldots, -1, 0, 1, \ldots, S$; τ_s and τ_z are the amounts of the pheromone corresponding the angles A_s and A_z, respectively.

A probability value is assigned to each discrete angle in both 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. Specifically, the probability *P(s)* assigned to the angle A_s is given by:

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

where τ_s is the amount of the pheromone corresponding the angle A_s and τ_s is in the range of $[0, 1]$.

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

$$\Theta_k(t) = \Theta_k(t-1) + \gamma A_s^* \tag{2}$$

where $\Theta_k(t)$ is the steering of movement of robot k at instant t, $\gamma \in [0,1]$ is the constant for smoothing of the steering direction adjusting and A_s^* is the selected direction by probability in (1).

The artificial agents in IAS-SS spread pheromone on a wide area in front of their respective positions, corresponding to sensor range area. The amount of the pheromone deposited on the ground decreases as the distance from the robot increases. Consider that L_t^k and $Q \in \mathbb{R}^2$ are the sensor range area at at iteration t and the entire environment space, respectively, such that $L_t^k \subset Q \subset \mathbb{R}^2$. Then, the amount of pheromone $\Delta_q^k(t)$, deposited by robot k on the position q at iteration t is:

$$\Delta_q^k(t) = (1 - \tau_q(t-1))\Gamma_q^k(t) \tag{3}$$

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

where q_k is the position of robot k; σ is the dispersion; $\delta \in (0,1)$ and $d(q,q_k)$ denotes the euclidean distance between q and q_k.

Furthermore, pheromone 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 such as follows:

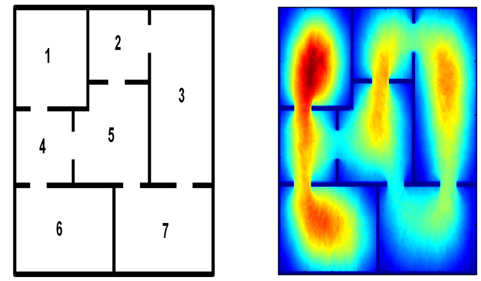
$$\Phi_q(t) = \rho \tau_q(t) \tag{5}$$

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

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

$$\tau_q(t) = (\tau_q(t-1) - \Phi_q(t-1)) + \sum_{k=1}^{N} \Delta_q^k(t) \tag{6}$$

In Fig. II, it is presented an example of the pheromone map. In Fig. II(a), it is showed the structure of the simulated environment, which is divided in 7 rooms. In Fig. II(b), it is illustrated the pheromone map obtained by a robot that started the exploration process from the room 1. In this example, the red color denotes a high concentration of the pheromone, whereas the blue color represents a low concentration of the substance.



(a) (b)

Fig. 2. Example of mapping: (a) Enviroment model; (b) Pheromone map

III. PHEROMONE MAP INTEGRATION METHOD

In the proposed approach, each robot is responsible for managing its pheromone concentration map, carrying out the release and evaporation operations when appropriate. Since each robot keeps a local map of pheromone concentration, a process of pheromone integration must be realized.

In an ideal situation, where the computational cost is not important, the pheromone integration can be performed assuming an unlimited communication range and that the robots exchange information among themselves at each iteration. If all robots share the pheromone information among themselves at each iteration, their pheromone grids will correspond to the global map of pheromone concentrations.

Given the characteristics of the current communication devices, the assumption of a communication radius able to connect all robots can be implemented through Wireless devices [28], [29]. In the virtual pheromone integration approach, the main problem is the computational time spent for the pheromone map sharing among all robots at each iteration.

The computational cost problem can be solved including a constraint that limits the information exchange to minimum intervals of iterations, named $it_{interval}$. Besides reducing the computational time of the system, this constraint decreases the redundant information exchange among the robots. Another factor that can be considered to reduce the cost of the approach is ensure that the robots share their pheromone maps only with these ones located within a communication radius R_C. The proposed approach assumes a limited communication radius among the robots, so a Wireless device can be applied for transmitting information about local maps between pairs of robots, considering indoor environments.

Since the process of steering direction adjusting of a robot R_k detects the pheromone concentrations at a specific distance R_D, only the robots near R_k could interfere on this decision of movement adjusting, through pheromone releasing.

The model of the sensor used on this method is similar to model described in Section 2 (Fig. 1). There is only one difference between the sensor model used in our approach and the sensor model proposed by Calvo et al. [16], [17], [18], which is the communication radius in the integration method. Since the robots will exchange information between themselves, each robot has a communication device which allows to identify other robots and to exchange local map information.

For a better comprehension of the pheromone map integration method, consider two adjacent robots R_i and R_j and their respective coordinate systems $\sum_i$ and $\sum_j$. Robot R_i sends R_j its coordinate system $\sum_i$ and its position (x_i, y_i) inside $\sum_i$. On the other hand, R_j sends R_i its coordinate system $\sum_j$ and its position (x_j, y_j) inside $\sum_j$. It is worth to notice that $\sum_i$ and $\sum_j$ are static.

Based on the perception between robots R_i and R_j, α_{ij} and α_{ji} are known for both robots, where α_{ij} is the orientation of R_i in coordinate system of R_j and α_{ji} is the orientation of R_j in coordinate system of R_i. The distance d_{ij} between robots R_i and R_j is also known. The relative orientation between robots R_i and R_j is denoted by θ_{ij}.

Next, a brief description of the integration process is presented. Consider a point P_k belonging to $\sum_i$, $P_k = (x_{P_k}, y_{P_k})$. The expected behavior of the proposed integration method is the definition of a new point $P_k^* = (x_{P_k^*}, y_{P_k^*})$, belonging now to $\sum_j$, such as the coordinates of P_k^* coincide to the same spacial area described by the coordinates of the point P. The proposed integration method is defined by:

$$\begin{bmatrix} x^*_{P_k} \\ y^*_{P_k} \end{bmatrix} = D(P_k, R_i) + \begin{bmatrix} x_j + d_{ij}\cos\alpha_{ji} \\ y_j + d_{ij}\cos\alpha_{ji} \end{bmatrix} \quad (7)$$

$$D(P_k, R_i) = \begin{bmatrix} \cos\theta_{ij} - \sin\theta_{ij} \\ \sin\theta_{ij} + \cos\theta_{ij} \end{bmatrix} * \left[\begin{bmatrix} x_{P_k} \\ y_{P_k} \end{bmatrix} - \begin{bmatrix} x_i \\ y_i \end{bmatrix} \right] \quad (8)$$

where $D(P_k, R_i)$ is the distance between the point P_k and the robot R_i, considering the rotation of the coordinate system of R_i according to relative angle θ_{ij}.

According to previous definition, the position P_k^* is established by three factors: 1) the position of robot R_j in its coordinate system; 2) the distance between two robots; and 3) the distance from the position P_k to the position of the robot R_i, considering the relative rotation of its coordinate system. It is worth to emphasize that proposed system by Tan et al. [27] does not consider the position of the robot R_j during the translation process of coordinates of the robot R_i.

IV. EXPERIMENTS AND RESULTS

Experiments are carried out in Player/Stage platform that models various robots and sensors. Although this platform includes navigation mechanism for obstacle avoidance, this behavior emerges in IAS-SS system only from consequence of the pheromone repulsive nature. The robot model used is the Pioneer 2DX equipped with a laser range-finder SICK LMS 200 able to scan the environment (general obstacles, e.g., walls and objects). Robots are able to map the environment using the method Occupancy Grid [30].

The system parameters used in the experiments are: $\sigma = 0.4R_D$ (pheromone releasing rate); $\rho = 10^{-4}$ (evaporation rate); $\tau_X(0) = 0.5$ (amount of pheromone at iteration $t = 0$); $R_D = 8.00$ 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 corresponds to 30% and 10% of size of S set, respectively; $R_{C_k} = 16$ (communication radius of robot R_k, k, k = 1, ..., N); maximum number of iterations of simulations = 1000. These parameter values correspond to those that the multiple robot system reaches the best performance, considering all previous experiments executed in [16], [17].The values assigned to parameters σ and ρ were defined through analysis of the performance in [18].

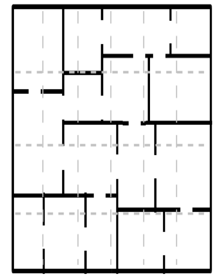


Fig. 3. Model of environment

Considering the integration process, the local map integrating is only started at iteration $t >= 100$. This restriction ensures that the robots obtain minimal information about the environment before to start the integration process. Since robot R_i joins its coordinate system with robot R_j, it is defined that robot R_i will wait 50 iterations to share again its local map with robot R_j, i.e.: $it_{interval} = 50$. This strategy decreases the redundant information exchange.

All experiments were executed 10 times. Thus, the average of the performances is computed to evaluate them. The discrete time is adopted in simulation and it is equivalent to the number of iterations. The environment model adopted is illustrated in Fig. 3. The environment where the multiple robot system carries out the exploration is divided in connected small regions called here *sectors*. The sectors are illustrated by the traced lines in Fig. 3. The adopted environment had been divided in 24 sectors. This division is a virtual mechanism for analysing the performance of the proposed method and, therefore, it is not used by the robots in any way.

A sector is said to be visited if it is reached by any robot. It is worth to note that if a robot is physically in a sector C_i and its sensors achieve both sector C_i and C_j, it is considered the robot visited only the sector C_i. The environment was set up for a dimension $30m \times 20m$. This area was represented by a matrix with dimension 375×375. The maximum number of iterations spends approximately $90min$ for simulating, then, each iteration of the simulation spends $5,4s$.

In Table I, it is presented the average of performance of the pheromone map integration method. This average corresponds to a variable on the interval $[0, 1]$ denotes the percentage of exploration of the environment. This variable denotes the relation between the amount of sectors represented by the map of each robot and the total amount of sectors of the environment. The amount of sectors represented by the map of each robot indicates both sectors visited by the robot and the sectors transferred to it through the map integration method proposed. In order to evaluate the integration process performance, experiments are carried out with an increasing number of robots in environment of Fig. 3. The robots start the navigation in top left area of the environment.

Moreover, the exploration process was tested using two different ways. In the first way, the integration module is active and the robots are able to exchange pheromone local maps among them, represented by Table I. In the second way, the integration module is inactive and the robots do not exchange maps with the others. Thus, the robots acquire pheromone information only about the sectors visited directly by themselves. This last configuration of experiments is presented in Table II.

Considering the case in which the integration module is active, the average of percentage exploration of the environment is increased while the number of robots increases. The increase of the average of exploration of the environment is caused by the greater pheromone information sharing among the robots. When the exploration system is executed without the integration process in IAS-SS strategy, the average of exploration keeps a similar value in all trials. Since the experiments are performed with a same amount of iterations, the robots tend to visit an amount of sectors with a same area, according to their local pheromone maps. Thus the average of exploration does not depend on the number of robots, when there is no integration.

The statistical difference between these two approaches is evaluated through a t-test. The relation between the calculated value for variable t and the tabled value for it is presented in Table III, considering a significance level $p = 0.05$. Since calculated t value is higher than tabled t value for each set of experiments, the null hypothesis is rejected in all the cases, indicating the average of exploration using the integration method is higher than the average of exploration without the integration. It is worth to notice that using only a single robot it is impossible performing the integration process, so there is no comparison between the system with and without integration in this case.

V. CONCLUSION AND FUTURE WORKS

In this work, a new local pheromone map integration method was proposed, which is based on inter-robot observations, considering the Inverse Ant System-Based Surveillance System strategy as method for environment exploration. In this method, the local map integrating is defined by transformation matrices, represented by the distance between two robot and their relative positions. The method is not dependent on the knowledge of the environment structure or initial positions of the robots.

A set of experiments were conducted for performance analysing. Two approach are considered and compared, one of them is the IAS-SS strategy without pheromone integration, and the other one is the IAS-SS with pheromone integration. The IAS-SS with integration is significantly superior, since the performance of mapping using the local map integration is higher than the performance without the integration. In our future works the exploration system will be tested in real environments using real robots.

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TABLE I

PERFORMANCE OF THE EXPLORATION PROCESS USING INTEGRATION - IAS-SS

Number of robots	R_1	R_2	R_3	R_4	R_5
1	0.40 ± 0.11	-	-	-	-
2	0.48 ± 0.14	0.50 ± 0.14	-	-	-
3	0.58 ± 0.10	0.59 ± 0.11	0.60 ± 0.11	-	-
4	0.60 ± 0.08	0.60 ± 0.08	0.60 ± 0.08	0.58 ± 0.08	-
5	0.63 ± 0.11	0.62 ± 0.10	0.62 ± 0.13	0.62 ± 0.10	0.62 ± 0.11

TABLE II

PERFORMANCE OF THE EXPLORATION PROCESS WITHOUT INTEGRATION - IAS-SS

Number of robots	R_1	R_2	R_3	R_4	R_5
1	0.40 ± 0.11	-	-	-	-
2	0.37 ± 0.17	0.41 ± 0.14	-	-	-
3	0.36 ± 0.15	0.42 ± 0.11	0.45 ± 0.17	-	-
4	0.39 ± 0.12	0.41 ± 0.10	0.38 ± 0.14	0.34 ± 0.13	-
5	0.41 ± 0.11	0.39 ± 0.13	0.38 ± 0.16	0.32 ± 0.12	0.41 ± 0.13

TABLE III

ANALYSIS OF PERFORMANCE WITH AND WITHOUT PHEROMONE INTEGRATION

Number of robots	Integration	Average (μ)	Pattern Deviation (σ)	Relation between t values
2	Yes	0.49	0.14	$>$
	No	0.39	0.15	
3	Yes	0.59	0.10	$>$
	No	0.41	0.14	
4	Yes	0.59	0.08	$>$
	No	0.38	0.12	
5	Yes	0.62	0.11	$>$
	No	0.38	0.12	

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