Territorial Marking for Improved Area Coverage in Anti-Flocking-Controlled Mobile Sensor Networks

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***Abstract*—Recently proposed distributed anti-flocking algorithms have enabled mobile sensor networks (MSNs) to deliver impressive area coverage performances. However, due to lack of information about each other's traverse history, mobile sensor nodes tend to travel extra distances to achieve 100% cumulative area coverage. Inspired by the territorial marking behaviour of solitary animals, this paper proposes a new information map and map updating methods for anti-flocking controlled MSNs. The proposed territorial marking anti-flocking control enables MSNs to achieve improved area coverage performances by encouraging nodes to remain in a part of the terrain. According to the results provided in this paper, the proposed algorithm can be more energy efficient for MSNs in continues monitoring applications.**

***Index Terms*—Mobile sensor networks, territorial marking, anti-flocking, area coverage, distributed control**

I. Introduction

Mobile sensor networks (MSN) are preferred over traditional wireless sensor networks in monitoring remote and hostile environments due to the added mobility which endorses them with the capabilities to perform self-deploying, self-organizing, and dynamic area coverage [1]–[3]. However, efficient motion control of MSNs are challenging due to the scale of networks and dynamic nature of environments. In monitoring applications, motions of mobile sensor nodes need to be controlled in such a way that they can maximize the area coverage collectively by minimizing overlaps and revisits. Many existing works [4]–[6] achieve dynamic area coverage by using fully coordinated motion control algorithms. However, the success of such algorithms heavily depends on task allocation and execution accuracies. Furthermore, they can be highly sensitive to initial conditions that cannot be guaranteed due to dynamic and uncertain nature of the outdoor environments, noisy sensors, and hardware malfunctions.

Recently, emergent motion control algorithms have been a popular choice for MSN motion control as they do not depend on prior task allocations and initial conditions [7]–[10]. Such algorithms unveils the true potential of MSNs by enabling their self-organizing and self-deploying capabilities. As a result, MSNs controlled by emergent motion control algorithms are more robust to sudden node removals, additions, and malfunctions. As a class of emergent motion control algorithms, anti-flocking algorithms have been proposed for enhancing the dynamic area coverage of an MSN in an area of interest (AoI). Miao *et al.* [7] first introduced rules of anti-flocking control inspired by the behavior of solitary animals to avoid collisions and maximize the area coverage. Later, Ganganath *et al.* [8], [10] proposed several fully distributed anti-flocking algorithms for mobile sensor networks using information maps.

Solitary animals stay away from their own species in many daily activities other than mating or caring of their offspring [7], [11]. Solitary animals usually forage solely to avoid sharing with others, thus maximize their chances of securing more foods. This selfish behavior has inspired anti-flocking controls of MSNs to achieve efficient area coverage performances by separating nodes from each other. Some of the solitary animals such as cheetahs and tigers use a strategy called territorial marking to identify their territories. It is also called as scent marking as it is mostly completed by depositing strong-smelling substances from dedicated scent glands, urine, or faeces [12]. Information maps has been used in anti-flocking-controlled MSNs to minimize the overlapping in explored areas [10]. However, as shown in Fig. 1, mobile nodes still tend to move in every part of an AoI to achieve complete area coverage which is contrary to efficient solitary animal behaviors. This results in mobile nodes having to traverse longer paths, thus spending more energy.

Inspired by the territorial marking behavior and efficient search strategies of solitary animals, a new type of information map, its corresponding updating process, and methods of using the new information map for improving area coverage performances are proposed in this paper. These proposals are incorporated with the distributed anti-flocking algorithm proposed in [10]. This new territorial marking anti-flocking control algorithm enables MSNs to achieve better area coverage performances compared to other existing anti-flocking algorithms. Moreover, this new algorithm remains to be fully distributed control and preserves three basic properties of anti-flocking control, *i.e.* collision avoidance, de-centering, and selfishness [7].

The rest of the paper is organized as follows. Section II briefly reviews the anti-flocking algorithm proposed in [10]. The territorial marking inspired information maps, their updating process, and the calculation process of selfishness goal locations are introduced in Section III. Section IV reports a simulation study to evaluate area coverage performances. Concluding remarks are given in Section V.

II. Distributed Anti-Flocking Control

The distributed anti-flocking algorithm with obstacle avoidance capabilities proposed in [10] is briefly reviewed here as the proposed territorial marking anti-flocking algorithm has been developed upon it. Consider an MSN with a set of N identical mobile sensor nodes. All nodes are assumed to carry isotropic radial sensors of range $r_s > 0$ and communication modules of range $r_c > 2r_s$. The MSN is modelled as a multi-agent system in which a set of α-agents $\mathcal{V}_\alpha = \{1, 2, \ldots, N\}$ represents mobile sensor nodes. Moreover, obstacles in the AoI and selfishness goals of α-agents are represented by β- and γ-agents, respectively. The position and velocity of an α-agent i at time t are denoted by q_i and p_i, respectively. The control input of α-agent i is given by

$$u_i = f_i^c + f_i^d + f_i^s, \tag{1}$$

where f_i^c, f_i^d, and f_i^s respectively represent the collision avoidance term, de-centering term, and selfishness term.

In (1), the collision avoidance term is defined as

$$f_i^c = h_i \bar{f}_i^c,$$

which is used to avoid collisions between α- and β-agents. A binary function h_i is defined as

$$h_i = \begin{cases} 1, & \text{if } \cos^{-1}\left(\frac{\bar{f}_i^c \cdot p_i}{\|\bar{f}_i^c\|\|p_i\|}\right) > \pi/2, \\ 0, & \text{otherwise,} \end{cases}$$

and $\bar{f}_i^c$ is defined as

$$\bar{f}_i^c = -\nabla_{q_i}\left(\sum_{k \in \mathcal{N}_i^\beta} \psi(\|q_k^\beta - q_i\|, d_\beta)\right).$$

Here, $\mathcal{N}_i^\beta$ is a set of β-neighbors of α-agent i, q_k^β is the position of β-agent k at time t, and d_β is the minimum desired distance gap between α- and β-agents. A nonnegative repulsive pairwise potential function is given by

$$\psi(z, d) = \begin{cases} \kappa_p \left[1 + \cos\left(\frac{\pi(z+d)}{2d}\right)\right], & \text{if } z \in [0, d], \\ 0, & \text{otherwise,} \end{cases}$$

where κ_p is a positive constant.

In (1), the de-centering term is defined as

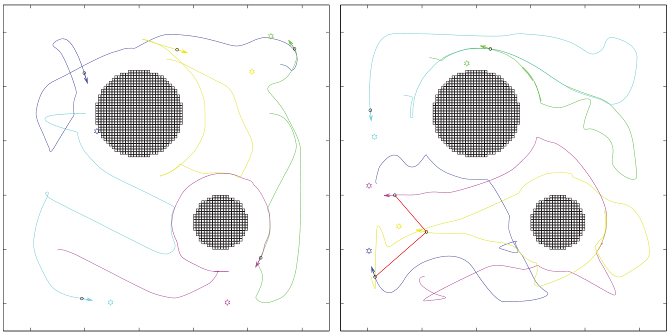
$$f_i^d = -\nabla_{q_i}\left(\sum_{j \in \mathcal{N}_i^\alpha} \psi(\|q_j - q_i\|, d_\alpha)\right),$$

where $\mathcal{N}_i^\alpha$ is a set of α-neighbors of α-agent i at time t. The minimum desired distance gap between α-agents is denoted by d_α.

In (1), the selfishness term is defined as

$$f_i^s = \kappa_s(q_i^\gamma - q_i) - \kappa_v p_i,$$

where κ_s and κ_v are positive constants. Here, q_i^γ is the position of a γ-agent of α-agent i at time t. The positions of γ-agents have a direct impact on the area coverage performances as they help to drive α-agents in the AoI. Thus, the positions of γ-agents need to be carefully calculated to improve area coverage performances.



(a) 1st full scan (b) 8th full scan

Fig. 1. Motion patterns of 5 mobile sensor nodes (α-agents) controlled by the distributed anti-flocking algorithm proposed in [10]. Circles, squares, and hexagons denote α-, β- and γ-agents, respectively. Arrowheads and curved trails represent moving directions and path history of α-agents during a full scan of the AoI. A connection between two connected α-agents is represented using a red colored straight line.

III. Territorial Marking for Distributed Anti-Flocking Control

A. Territorial Marking Inspired Information Maps

It is assumed that each α-agent carries its own information map which consists of the sensing history of an AoI. For the ease of representation, the AoI is first discretized into a set of square cells as shown in Fig. 2. Let the center coordinates of all cells be denoted by a set X and the local information map of α-agent i be denoted by m_i. Thereon, $m_i(x)$ carries two pieces of information about the cell centered at $x \in X$: 1) when the cell was last visited and 2) who visited it.

At time $t = 0$, all local information maps are set to their default values such that

$$m_i(x) = [0, i],$$

for all $i \in \mathcal{V}_\alpha$ and for all $x \in X$. As time evolves and α-agents keep moving in the AoI, all local information maps are updated such that

$$m_i(x) = [t, i],$$

if $\|x - q_i\| < r_s$ for all $i \in \mathcal{V}_\alpha$ and for all $x \in X$ at time $t > 0$.

Apart from updating local information maps with their sensing history, α-agents exchange their information maps as they communicate with other α-agents. Suppose α-agent i is connected with α-agent j at time t, *i.e.* $\|q_i - q_j\| < r_c$. Then α-agent i receives the local information map of α-agent j and updates its local information map based on the information maps of both the agents as below:

Step 1. For any $x \in X$, set $m_i(x) = m_j(x)$ if $m_j(x)$ carries more recent information compared to those of $m_i(x)$.

Step 2. Find a subset $X' \subset X$ such that $m_i(x') = [t', i]$ and $m_j(x') = [t', j]$ for time $t' \leq t$ and for all $x' \in X'$.

Step 3. For all $x' \in X'$, set $m_i(x') = [t', i]$ if $\|x' - q_i\| \leq \|x' - q_j\|$ and $m_i(x') = [t', j]$ otherwise.

Similarly, α-agent j receives the local information map of α-agent i and updates its local information map based on both

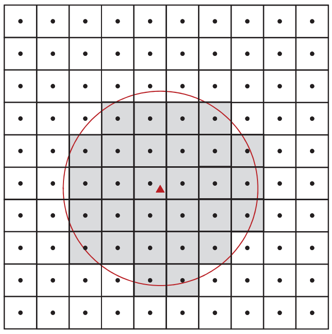


Fig. 2. An example for a discretized AoI. The red color triangle represents an α-agent and the red color circle around it represents its sensing coverage. Black dots represent the center points of each cell of the discretized AoI. If the center point of a cell is under the sensing coverage of an α-agent, the corresponding cell is considered as being covered by that α-agent. Hence, in this illustration, the gray colored cells are covered, but not the white colored cells.

information maps. Step 1 ensures that both information maps carry latest information. The rest of the steps focus on the areas that have visited by both agents at the same time. Those areas are allocated according to the current proximity of α-agents.

Direct exchanges of information maps lead to indirect communication of α-agents' sensing history. Assume that α-agent i connects with α-agent j and later α-agent i connects with α-agent k. Even though α-agent k has never communicated with α-agent j before, α-agent k may still receive a part of the sensing history of α-agent j via the information map of α-agent i. Such indirect communication makes the information spreading faster throughout an MSN.

B. Calculation of γ-Agent Positions

The territorial marking inspired information maps are used to calculate the positions of γ-agents. Let $\delta(t, m_i(x))$ be the elapsed time since the cell centered at x has been last covered by an α-agent according to the information map m_i of α-agent i. To calculate q_i^γ, m_i is first evaluated using

$$\xi_i(m_i, x, t) = \delta\big(t, m_i(x)\big)\big(\rho + (1-\rho)\lambda_i(x)\big).$$

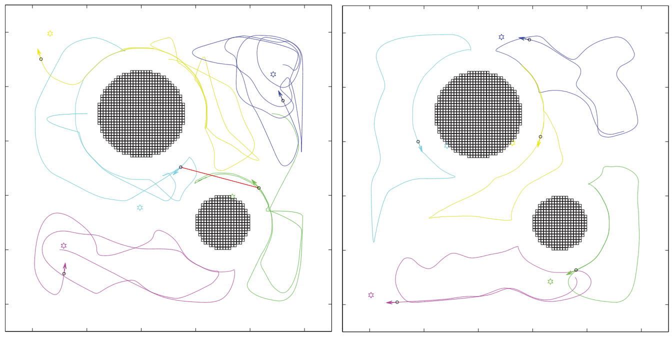
Here, $0 < \rho < 1$ and $\lambda_i(x)$ is given as

$$\lambda_i(x) = \exp\{-\sigma_1(\|q_i - x\| + d_{\mathrm{v}}) - \sigma_2\|q_i^\gamma - x\|\},$$

where σ_1 and σ_2 are positive constants. A virtual distance d_{v} is equal to 0 if the cell centered at x has been last marked by α-agent i according to m_i, otherwise it is equal to a positive constant. Here, d_{v} is used to discourage α-agents to visit other α-agents' territories by virtually increasing distance to them. α-agents should visit the locations that have the highest values of $\xi(x, t)$ first. Hence, $q_i^\gamma(t+1)$ is selected as

$$q_i^\gamma(t+1) = \underset{x \in \widetilde{X}_i}{\arg\max}\, \xi_i(m_i, x, t),$$

where $\widetilde{X}_i = \{x | x \in X, \|x - q_j\| \geq \|x - q_i\| > r_s, j \in \mathcal{N}_i^\alpha\}$ [10]. Three recalculation criteria for q_i^γ were introduced in [10] and they have been adopted in the proposed anti-flocking algorithm without any changes.



(a) 1st full scan (b) 8th full scan

Fig. 3. Motion patterns of 5 α-agents controlled by the proposed territorial marking anti-flocking control algorithm. All settings remained same as the experiment reported in Fig. 1

C. Basic Properties of Proposed Algorithm

The proposed territorial marking anti-flocking algorithm encourages α-agents to first mark its territory and then confine itself to the marked territory in the subsequent searches. However, if some cells are left out for a considerable time period by a marked α-agent, nearby α-agents tend to cover and remark those areas to avoid coverage holes. Furthermore, α-agents tend to cover areas marked by other α-agents if they are not aware of the recent sensory information of those areas due to lack of communication with other α-agents. In order to illustrate these properties, the experiment reported in Fig. 1 was reconducted using the proposed territorial marking anti-flocking algorithm and results are illustrated in Fig. 3. The results reported in Fig. 3 also illustrate the obstacle avoidance capabilities of the proposed algorithm.

IV. Area Coverage Evaluations

A. Simulation Set-up

To further evaluate area coverage performances of the proposed algorithm against existing distributed anti-flocking algorithms [8], [10], extensive simulations were carried out using MATLAB on a computer with Intel Core i5-6200U CPU, 16GB of RAM, and Microsoft Windows 10.

In the simulation study, a square obstacle-free AoI with an area of 1600 m^2 was considered. The AoI was discretized into 0.5×0.5 m^2 cells to create its information map. Initially, α-agents were assumed to be distributed uniformly at random in the AoI. Their initial velocities were picked uniformly at random from the box $[-1, 1]^2$ ms^{-1}. Throughout all the simulations, following parameters remained same: $r_s = 5$ m, $r_c = 15$ m, $d_{\mathrm{v}} \in \{0, 20\}$ m, $\kappa_p = 15$, $\kappa_s = 0.1$, $\kappa_v = 0.6$, $\rho = 0.2$, $\sigma_1 = 0.04$, $\sigma_2 = 0.01$, $d_\alpha = 9$ m, and $d_\beta = 4.5$ m.

B. Simulation Results

The first set of simulations was conducted to investigate the average distance travelled by α-agents to achieve 100% cumulative area coverage, *i.e.* a full scan. The simulation results are illustrated in Fig. 4. According to the results, the algorithm proposed in [10] outperforms the other algorithms by maneuvering α-agents to travel shorter distances for the

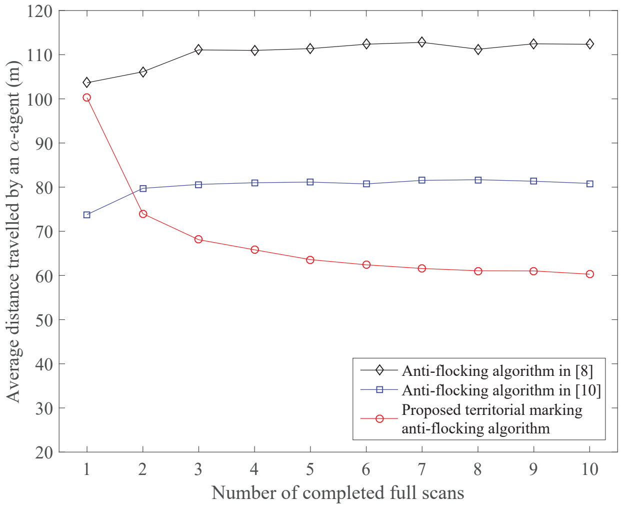


Fig. 4. Average distance travelled by an α-agent in MSNs of size 5 to complete a full scan versus the number of completed full scans. All data points were obtained by averaging results from 1000 simulations.

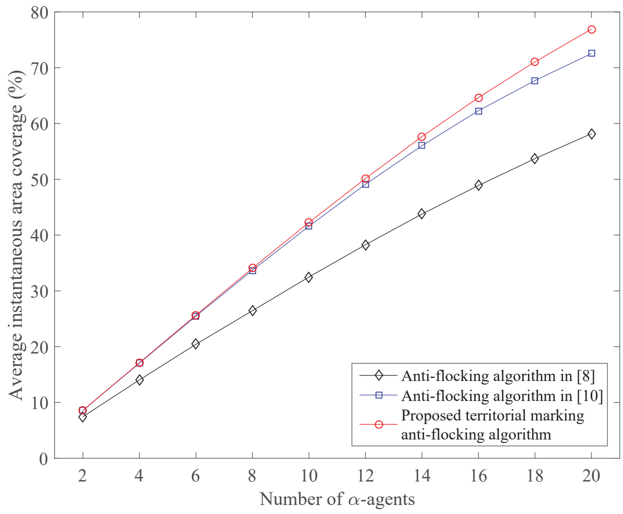


Fig. 5. Average instantaneous area coverage of MSNs versus the network size. All data points were obtained by averaging results from 1000 simulations.

first full scan. As expected, α-agents controlled by the proposed algorithm travelled longer distances initially to mark their territories. However, in subsequent full scans, α-agents controlled by the proposed algorithm travelled considerably shorter distances to achieve a full scan. For the 10^{th} full scan, an α-agent controlled by the proposed algorithm travelled nearly 75% and 54% of the average distances travelled by α-agents controlled by the algorithms proposed in [10] and [8], respectively. MSNs controlled by the proposed algorithm can be more energy saving in continuous monitoring applications.

The second set of simulations was conducted to evaluate instantaneous area coverage performances of the algorithms under test. The simulation results are illustrated in Fig. 5. According to the results, the algorithms proposed in this paper and [10] outperform the algorithm proposed in [8] in terms of instantaneous area coverage. The former two algorithms performed almost the same for small-scale networks. However, the proposed algorithm delivered better performances compared the algorithm in [10] as the network size increased. This is due to the sensory coverage overlap minimization capabilities of the proposed algorithm.

V. Conclusion

A new distributed anti-flocking algorithm with territorial marking capabilities is proposed for MSNs. The main contributions of the proposed algorithms are the territorial marking inspired information maps, a map updating process, and methods of using the new information map for improving area coverage performances. Territorial marking helps MSNs to minimize overlaps of sensory coverage of individual sensors. The proposed algorithm has enabled MSNs to achieve better area coverage performances compared to some existing distributed anti-flocking algorithms. The proposed algorithm can be more beneficial for large-scale MSNs utilized in continues monitoring operations.

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