Distributed Anti-Flocking Algorithms for Dynamic Coverage of Mobile Sensor Networks

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***Abstract*—Mobile sensor networks (MSNs) are often used for monitoring large areas of interest (AoI) in remote and hostile environments which can be highly dynamic in nature. Due to the infrastructure cost, MSNs usually consist of limited number of sensor nodes. In order to cover large AoI, the mobile nodes have to move in an environment while monitoring the area dynamically. MSNs that are controlled by most of the previously proposed dynamic coverage algorithms either lack adaptability to dynamic environments or display poor coverage performances due to considerable overlapping of sensing coverage. As a new class of emergent motion control algorithms for MSNs, anti-flocking control algorithms enable MSNs to self-organize in an environment and provide impressive dynamic coverage performances. The anti-flocking algorithms are inspired by the solitary behavior of some animals who try to separate from their species in most of daily activities in order to maximize their own gains. In this paper, we propose two distributed anti-flocking algorithms for dynamic coverage of MSNs, one for obstacle free environments and the other one for obstacle dense environments. Both are based on the sensing history and local interactions among sensor nodes.**

***Index Terms*—Mobile sensor networks, dynamic coverage, distributed control, anti-flocking, information maps, obstacle avoidance**

I. Introduction

WIRELESS sensor networks (WSNs) have been widely used for monitoring areas of interest (AoI) in many applications [1], [2]. Traditional WSNs consist of stationary sensor nodes which are capable of sensing, computing, and communicating cooperatively. Once stationary sensor nodes are deployed in an AoI, they cannot be rearranged easily. In order to achieve a complete area coverage using a stationary WSN, there should be a surplus number of sensor nodes depending upon the size of the AoI and the sensing range of each sensor. Moreover, they should be deployed in such a manner that there are no coverage holes exist. Unfortunately, WSNs are commonly utilized in applications in which manual sensor deployment can be difficult [3] and the network size reduces over time due to malfunctioning and battery drainage of sensor nodes [4]. Mobile sensor networks (MSN) overcome drawbacks of their stationary counterparts using mobile sensor nodes which are capable of repositioning and reorganizing themselves in the network to cope with rapid topology changes. A MSN can initiate with an arbitrary initial distribution and diffuse in an AoI to collect information.

Li et al. proposed two MSN self-deployment algorithms for constructing focused coverage around a given point of interest [5]. The algorithms proposed in [5] give higher coverage priority to areas close to the point of interest compared to distant areas. Some early attempts in achieving uniform coverage of MSNs have focused on deploying sensor nodes to desired locations using artificial potential fields [6] or virtual force fields [7]. Derr and Manic proposed two algorithms to determine an optimal configuration for WSNs. Their first algorithm is based on a centralized approach which is capable of generating mesh network configurations to achieve 100% area coverage [8]. In their second algorithm, a decentralized approached was proposed to achieve adaptive coverage in mesh networks by dynamically adjusting the sensing range of the sensor nodes [9]. Mahboubi et al. proposed several algorithms based on Voronoi diagrams for improving sensor network coverage [10], [11]. The algorithm proposed in [10] utilizes multiplicatively weighted Voronoi diagrams to detect coverage holes. Once detected, mobile sensors are moved in appropriate directions to minimize the size of the coverage holes. In [11], edge-based and vertex-based movement strategies were proposed in order to steer sensor nodes towards coverage holes. Cheng and Savkin proposed a decentralized control algorithm for MSNs to achieve optimal blanket coverage between two arbitrary boundaries [12]. The generated sensor lattice ensures a minimum number of sensors required to achieve full coverage.

A. Dynamic Coverage of Mobile Sensor Networks

Dynamic coverage algorithms control the motion of MSNs such that they can monitor a large AoI over time with a limited number of sensor nodes. These algorithms can be categorized under three main categories [13]: fully coordinated motion control algorithms, fully random motion control algorithms, and emergent motion control algorithms.

Fully coordinated motion control algorithms can be further categorized into two types [13]. The first type of coordinated motion control algorithms divide an AoI into a number of sections according to the number of mobile sensor nodes in the network such that overlapping between these sections is minimized. Each sensor is responsible for the coverage of a particular section. A Voronoi diagram based solution is proposed in [14]. The second type of algorithms form a team

Manuscript received June 26, 2015; revised November 26, 2015; accepted January 11, 2016. This work is supported by the Hong Kong PhD Fellowship Scheme (Project RTKL) and the Department of Electronic and Information Engineering, the Hong Kong Polytechnic University (Project G-YBKH).

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of mobile sensor nodes which coordinately search over an AoI [15]. A coordinated sensor patrolling algorithm was proposed in [16] to identify the intruders that attempt to enter an AoI. Fully coordinated control algorithms rely on proper task allocations and accurate executions of allocated tasks by the sensor nodes. Proper task allocations can be effective only in fully known static environments. Nevertheless, accurate executions of the tasks heavily depend on localization and navigational accuracy of the sensor nodes which are often erroneous due to noise and hardware faults. In general, fully coordinated motion controlled MSNs are less robust to node failures as such failures will result in coverage holes. Furthermore, these systems are less scalable as they need to be reconfigured when the number of sensor nodes is varied.

Fully random motion control algorithms enable mobile sensor nodes to move within AoI in random directions below a maximum velocity [17], [18]. The cumulative area coverage over a period of time depends on the motion speed and sensing range of the sensor nodes. Higher speeds of the nodes may lead to higher accumulated area coverage, but many places will be left uncovered if the sensing frequency is too low. Lie et al. proposed a random motion control model for dynamic coverage of MSNs, which enable sensor nodes to move in straight lines in random directions till they hit the boundary of the AoI [19]. They showed that their proposed system can achieve complete area coverage as time goes to infinity. Random motion controlled MSNs take longer time to cover a given area compared to the coordinated motion controlled MSNs operating at the same speed, mainly due to a considerable overlapping of sensing coverage. On the other hand, they are more robust to node failures and exhibit better adaptability and scalability in compared to fully motion controlled MSNs.

In contrast to coordinated and random motion control algorithms, emergent motion control algorithms allow mobile sensor nodes to self-organize themselves within the network using local interactions. Such self-organizing systems often based on simple rules to achieve their objectives without complete information about the environment. Many examples for self-organizing systems can be found in nature, such as bacteria swarms, bird flocks, and fish schools. Reynold described the collective behavior of these animal groups using three heuristic rules: flock centering, collision avoidance, and velocity matching [20]. Inspired by collective behaviors of animals, many researches developed flocking control algorithms which enabled self-organizing behaviors for multi-agent systems [21]–[23]. In MSNs, flocking control algorithms are commonly used for steering a group of sensor nodes to track a dynamic target. However, in this work, our focus is on dynamic area coverage which is a different application of MSNs.

B. Anti-Flocking Control

Contrary to the collective behavior of birds and fishes, some animals such as spiders, tigers, and chipmunks attempt to separate from each other while foraging and securing space for themselves. In [13], Miao et al. described the behavior of these solitary animals using the term *anti-flocking* and also introduced three heuristic rules to describe their dynamics: *selfishness*, *de-centering*, and *collision avoidance*. The objective of the first rule is to move individuals in a group toward a direction which maximizes their own gains. In de-centering, they attempt to be away from each other. Finally, those individuals attempt to avoid collisions with nearby obstacles. Based on the rules of both flocking and anti-flocking, a semi-flocking algorithm was proposed to enable MSNs to perform both dynamic coverage and target tracking interspersedly [24]. In [25], we proposed a distributed anti-flocking algorithm for dynamic MSNs by introducing mathematical interpretations to the heuristic rules proposed in [13]. Fully distributed control of sensor nodes is achieved using *information maps* which are used to keep track of sensing history of mobile sensor nodes. The concept of the information maps has been motivated by the territorial marking behavior of solitary animals. Simulation results given in [25] show that, under certain conditions, the proposed distributed anti-flocking algorithm can steer mobile sensor nodes to cover a given AoI in a similar time duration as a centralized control counterpart.

C. Contributions and Organization of the Paper

In this paper, we propose two novel distributed anti-flocking algorithms for MSNs to dynamically cover a given AoI with a limited number of sensor nodes. The proposed algorithms are solely based on sensing history of mobile sensor nodes and information collected through local interactions among the sensor nodes. In order to facilitate the information transfer between sensor nodes, we introduce a simplified version of distributed information maps. These distributed information maps are used in both of the proposed algorithms to minimize overlapping sensing coverage. The first algorithm is designed for dynamic coverage in obstacle free environments. The sensor nodes that are controlled under this algorithm try to avoid collisions with each other while navigating in the environment. Based on their distributed information maps, their selfishness goals are chosen to enhance the cumulative area coverage while minimizing the overlapping of the sensing coverage. The second algorithm is designed for dynamic coverage in obstacle dense environments. Besides the main control objectives of the first algorithm, this algorithm tries to control the sensor nodes such that they avoid collisions with obstacles in the environment. In addition to the sensing history of sensor nodes, the proposed distributed information maps are used to store information about obstacles. Based on the information maps, an agent based technique is developed for obstacle avoidance while anti-flocking. The proposed algorithms were proven to satisfy the objectives of the three anti-flocking rules. Furthermore, a simulation study was carried out to analyze and compare their coverage performances.

The rest of the paper is organized as follows. In Section II, we recall some background materials on the topology of mobile sensor networks and introduce the concept of distributed information maps. A novel free-space anti-flocking algorithm is proposed and analysed in Section III. Anti-flocking with obstacle avoidance capability is proposed and analysed in Section IV. Results and discussions are given in Sections V and VI. Some concluding remarks are given in Section VII.

II. Preliminaries

A. Topology of Mobile Sensor Networks

The anti-flocking algorithms presented in this paper consider a group of N mobile sensor nodes moving in a convex region in $\mathbb{R}^2$. All the nodes are equipped with identical and isotropic radial sensors of range $r_s > 0$. Each sensor node has an isotropic radio communication module of range r_c, which is assumed to be identical for all the mobile nodes. In this work, we assume that $r_c > 2r_s$, which enables sensor nodes to communicate with each other without overlapping their sensing area. However, in general, r_s and r_c can be chosen independently. Inspired by Olfati-Saber's flocking algorithms [21], we label to a mobile sensor node as an α-*agent*. (Later, we introduce virtual agents called β-*agents* and γ-*agents* to model the effects of obstacles and selfishness, respectively.) Dynamics of α-agents are given by

$$\begin{cases} \dot{q}_i(t) = p_i(t), \\ \dot{p}_i(t) = u_i(t), \qquad i = 1, 2, \ldots, N, \end{cases} \tag{1}$$

where $q_i(t), p_i(t), u_i(t) \in \mathbb{R}^2$ are the position, velocity, and control input of agent i at time t. For notational convenience, we often use $q_i(t) = q_i$, $p_i(t) = p_i$, and so on. We also take $q = [q_1 \ q_2 \ \ldots \ q_N]^{\mathrm{T}}$ and $p = [p_1 \ p_2 \ \ldots \ p_N]^{\mathrm{T}}$ [22].

An α-agent can communicate with other α-agents within its communication range. The set of α-*neighbors* of α-agent i at time t is denoted as

$$\mathcal{N}_i^{\alpha}(t) = \{ j : \|q_j - q_i\| < r_c, j = 1, 2, \ldots, N, j \neq i \},$$

where $\|\cdot\|$ is the Euclidean norm in $\mathbb{R}^2$. Since r_c is identical for all the agents, $j \in \mathcal{N}_i^{\alpha}(t) \Leftrightarrow i \in \mathcal{N}_j^{\alpha}(t)$. As time evolves, α-agents move according to Eq. (1), which results in changes in $\mathcal{N}_i^{\alpha}(t)$. Due to symmetry, interactions among α-agents can be represented using an undirected dynamic graph $\mathcal{G}_{\alpha}(t) = \{\mathcal{V}_{\alpha}, \mathcal{E}_{\alpha}(t)\}$. Here, $\mathcal{V}_{\alpha}$ is a set of vertices which can be defined as $\mathcal{V}_{\alpha} = \{1, 2, \ldots, N\}$. Elements of $\mathcal{V}_{\alpha}$ represent α-agents in the group. Neighboring relations between α-agents are represented by using a set of edges $\mathcal{E}_{\alpha}(t) \subseteq \mathcal{V}_{\alpha} \times \mathcal{V}_{\alpha}$ which can be denoted as $(i, j) \in \mathcal{E}_{\alpha}(t) \Leftrightarrow i \in \mathcal{N}_j^{\alpha}(t)$ [21], [22].

B. Repulsive Pairwise Potential

We define a non-negative repulsive pairwise potential as

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

The pairwise potential $\psi(z, d)$ reaches its maximum as $z \to 0$, smoothly vanishes to 0 as $z \to d$, and remains at 0 over the interval $[d, \infty)$. Later, we use $\psi(z, d)$ to define a collective potential function for α-agents.

C. Distributed Information Maps

We introduce a novel and simplified version of the information maps for distributed anti-flocking of mobile sensor nodes. Let m_i be the information map of α-agent i. Similar to our previous work [25], we also represent m_i as a discretized field with similar dimensions to the AoI. Each cell in m_i at time t is denoted by $m_i(x)$ where x is the center coordinate of the cell and let X be a set of all such x values within a given AoI. Here, $m_i(x)$ carries the information on the time that a location x has been last visited. At the beginning, information maps of all the sensor nodes need to be initialized to their default values, i.e. $m_i(x) = 0$ for all $x \in X$ and $i \in \mathcal{V}_{\alpha}$. As α-agents keep exploring the AoI, their information maps are being updated such that

$$m_i(x) = t, \tag{3}$$

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

So far, we have explained how individual maps being updated locally as time evolves. However, if $\mathcal{N}_i^{\alpha} \neq \emptyset$, α-agent i can exchange its information map with α-agent $j \in \mathcal{N}_i^{\alpha}$ and update $m_i(x)$ for all $x \in X$ such that

$$m_i(x) = m_j(x), \tag{4}$$

if $m_j(x) > m_i(x)$. Using this methods, α-agent i can keep the track of up-to-date information on its sensing history as well as those of other α-agents that it has communicated with. In addition to that, α-agent i might get access to the sensing history of its non-neighbors indirectly. Assume that α-agent k has not been a neighbor of i for $t > 0$. Hence, i has not had direct access to k. However, if $k \in \mathcal{N}_j^{\alpha}(t_1)$ and $j \in \mathcal{N}_i^{\alpha}(t_2)$ for $t_2 > t_1 > 0$, α-agent i can receive an alternated sensing history of α-agent k through m_j since j and k have exchanged their information previously.

Fig. 1 illustrates the concept of information map exchange between two α-agents. In the given setup, $r_s = 4$ m and $r_c = 10$ m. AoI is a square shaped region with dimensions 20×20 m^2. At $t = 0$, two α-agents initiate from arbitrary locations in the AoI and update their information map as explained above based on their sensing coverage. As time evolves, they keep moving in the environment while updating their information maps. At $t = 3$ s, they locate within the communication range of each other, thus, they exchange the information maps with their neighbor and update their information maps as explained above. Since the proposed information maps carry information on the sensing history of α-agents, these information can be used to minimize the overlapping sensing area effectively. In the proposed algorithms, we use these information maps to select selfishness goals of α-agents to maximize individual area coverage.

III. Free-Space Anti-Flocking

In this section, we present a distributed algorithm for mobile sensor network to perform anti-flocking in free-space. Formulations of this algorithm are partially inspired by Olfati-Saber's flocking algorithms [21]. In the proposed free-space anti-flocking algorithm, the control input of α-agent i consists of two terms

$$u_i = f_i^d + f_i^s, \tag{5}$$

where f_i^d and f_i^s are the de-centering term and selfishness term, respectively.

The de-centering term f_i^d is aimed to regulate distance between α-agents. Thus, the same term is indirectly responsible for collision avoidance among α-agents. In this work,

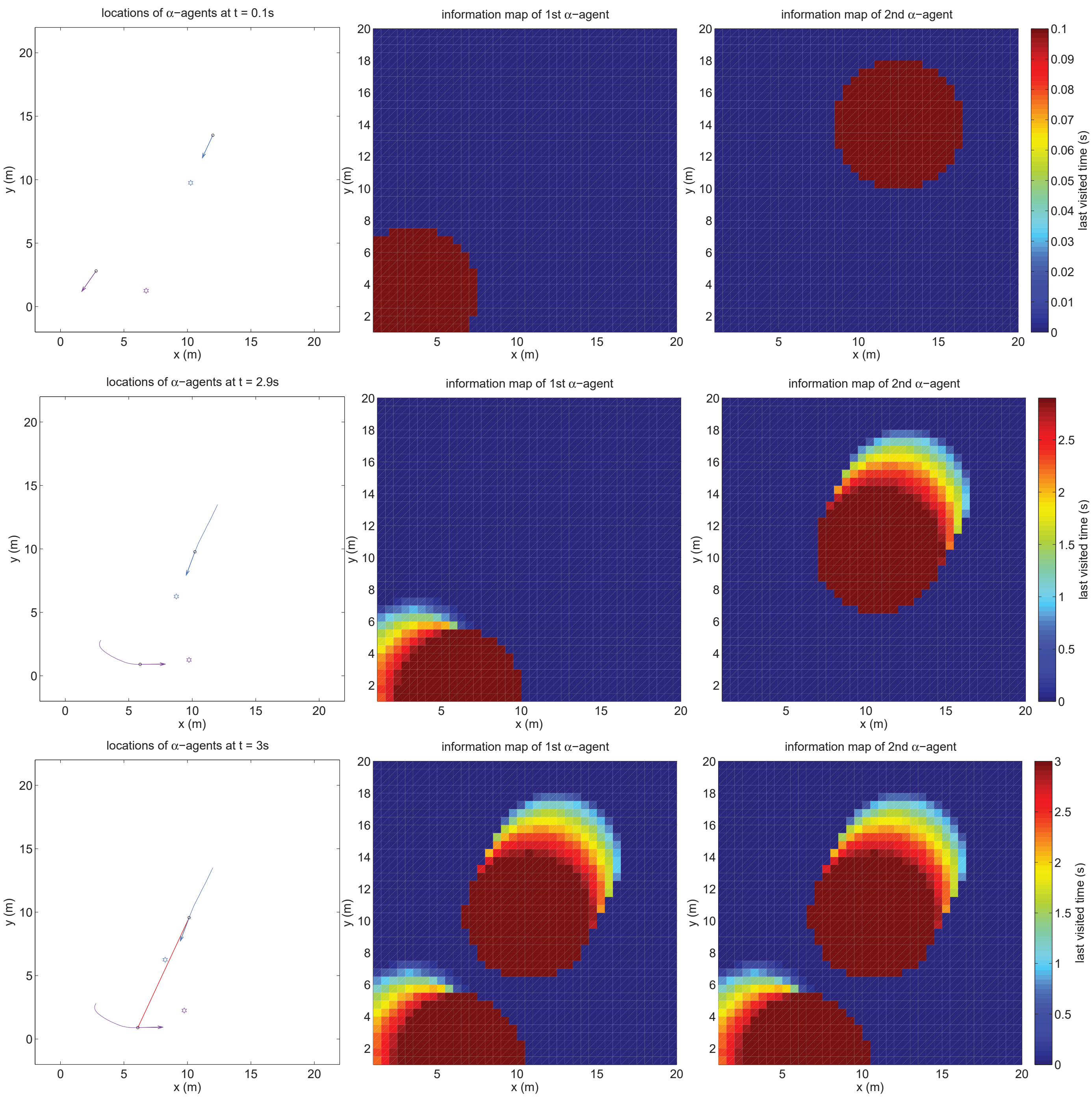

Fig. 1. An illustration of information map exchange between two α-agents. In the physical maps (1st column), circles and hexagons denote α- and γ-agents, respectively. Arrowheads and curved trails represent moving directions and path history of α-agents. A connection between two α-agents is represented using a red colored straight line.

de-centering among α-neighbors is achieved using a virtual potential field

$$f_i^d = -\nabla_{q_i} V_i^\alpha(q). \tag{6}$$

Here, $V_i^\alpha(q)$ is a collective potential function based on the relative distance between α-agent i and its neighbors. It can be defined using the repulsive pairwise potential function given in Eq. (2) as

$$V_i^\alpha(q) = \sum_{j \in \mathcal{N}_i^\alpha} \psi(\|q_j - q_i\|, d_\alpha),$$

where d_α $(0 < d_\alpha \leq 2r_s)$ is the minimum desirable distance between α-agents. Selecting $d_\alpha > 2r_s$ may result in coverage holes.

The selfishness term f_i^s in Eq. (5) is responsible for maximizing the area coverage of each α-agent. In order to maximize the area coverage, the selfishness goals should be defined such that each agent steer towards less visited areas in the given AoI. We introduce static virtual agents called γ-agents to steer α-agents towards their selfishness goals. Every α-agent has a corresponding γ-agent. They cannot communicate among themselves. If the position of γ-agent of α-agent i at time t is q_i^γ, then f_i^s can be defined as

$$f_i^s = \kappa_s(q_i^\gamma - q_i) - \kappa_v p_i, \tag{7}$$

where κ_s and κ_v are positive constants. Using Eqs. (6) and (7), the control input given in Eq. (5) can be rewritten as

$$u_i = -\sum_{j\in\mathcal{N}_i^\alpha} \nabla_{q_i}\psi(\|q_j - q_i\|, d_\alpha) + \kappa_s(q_i^\gamma - q_i) - \kappa_v p_i. \tag{8}$$

A. Calculation of Position of γ-agents

Since the main objective of the proposed anti-flocking algorithm is to maximize dynamic area coverage of a given AoI, the positions of γ-agents should be selected in such a way that they would maximize the cumulative area coverage and minimize the overlap of each others sensing coverage. The information maps introduced in Section II-C can be utilized to decide the position of their γ-agents effectively. Given the information map m_i of α-agent i at time $t > 0$, we introduce a benefit function $\xi_i(x,t)$ to evaluate m_i, which is given by

$$\xi_i(x,t) = \big(t - m_i(x)\big)\big(\rho + (1-\rho)\lambda_i(x)\big). \tag{9}$$

The term $\big(t - m_i(x)\big)$ is the time span after the location x has been last visited. A high value indicates that the corresponding location has not been visited recently. The function $\lambda_i(x)$ is given by

$$\lambda_i(x) = \exp(-\sigma_1\|q_i - x\| - \sigma_2\|q_i^\gamma - x\|), \tag{10}$$

where σ_1 and σ_2 are positive constants. In Eq. (9), ξ_i can be considered as a quantitative measure of preference for selecting position $x \in \widetilde{X}_i$ as q_i^γ. Hence, we select $q_i^\gamma(t+1)$ such that it maximizes $\xi_i(x,t)$, i.e.

$$q_i^\gamma(t+1) = \underset{x\in\widetilde{X}_i}{\arg\max}\, \xi_i(x,t), \tag{11}$$

where $\widetilde{X}_i = \{x | x \in X, \|x - q_j\| \geq \|x - q_i\| > r_s, j \in \mathcal{N}_i^\alpha\}$.

Suppose q_i^γ is calculated at time t_1, then α-agent i keeps steered by control protocol given in Eq. (8) and it will recalculate the position of its γ-agent at time $t_2 > t_1$ if one of the following criteria is fulfilled:

1) q_i^γ is covered by α-agent i, i.e. $\|q_i^\gamma - q_i\| \leq r_s$.
2) α-agent i connects to α-agent $j \in \mathcal{V}_\alpha$ whose information map indicates that q_i^γ has been covered at time $t_3 \in (t_1, t_2)$. (Here, q_i^γ could have been covered by j, itself, or an α-neighbor of j within the time period of (t_1, t_2).)
3) α-agent i connects to α-agent $j \in \mathcal{V}_\alpha$ whose γ-agent locates within a circle centered at q_i^γ and with a radius of r_s, i.e. $\|q_i^\gamma - q_j^\gamma\| \leq r_s$, and $\|q_j - q_j^\gamma\| < \|q_i - q_i^\gamma\|$. (In other words, if two α-neighbors has their γ-agents located within a range of r_s, whoever closer to its γ-agent gets the priority.)

If any of the above criteria is fulfilled, q_i^γ is recalculated according to Eq. (11). And finally,

4) if α-agent i connects to α-agent $j \in \mathcal{V}_\alpha$, while $\|q_i^\gamma - q_j\| < \|q_i^\gamma - q_i\|$ and $\|q_j^\gamma - q_i\| < \|q_j^\gamma - q_j\|$, then i and j swap the positions of their γ-agents.

If we glance back at the four criteria given above, the first and second criteria ensure that an α-agent keeps exploring new locations. The third criterion ensures that two α-neighbors will not chase after their γ-agents that are close to each other, which can ultimately result in overlapping of their sensor coverage. The forth criterion tries to minimize the traveling distance of each agent by swapping the locations of their γ-agents, which ultimately results in assigning a closer goal to everyone.

B. Analysis of Free-Space Anti-Flocking

The main objectives of the proposed free-space anti-flocking are keeping α-agents away from each other to avoid collisions and steering them towards their selfishness goals which ultimately help to reach full area coverage in a shorter time.

In order to analyze the collision avoidance capability of the proposed algorithm, an energy function is defined for a group of α- and γ-agents that are applying control protocol given in Eq. (8) as the sum of their potential energy and kinetic energy [22], that is

$$Q(p,q) = \sum_{i=1}^{N}\left(\frac{1}{2}U_i(q) + K_i(p)\right). \tag{12}$$

Here, the potential energy of α-agent i can be defined as

$$U_i(q) = V_i^\alpha(q) + \kappa_s(q_i^\gamma - q_i)^{\mathrm{T}}(q_i^\gamma - q_i), \tag{13}$$

and the kinetic energy as

$$K_i(p) = \frac{1}{2}p_i^{\mathrm{T}}p_i. \tag{14}$$

Lemma 1: The energy $Q(p,q)$ of a group of α- and γ-agents that are applying control protocol given in Eq. (8), is a non-increasing function of time t for given positions of γ-agents. *(Proofs of all the lemmas and theorems are given in APPENDIX 1 in [26])*

We use this non-increasing characteristic of $Q(p,q)$ to show that the proposed free-space anti-flocking algorithm can avoid collisions among α-agents under certain conditions.

Theorem 1: In a group of N α-agents that are applying control protocol given in Eq. (8), α-agents do not collide with each other at any given time $t > 0$ if the initial energy of the system is less than κ_p for given positions of γ-agents.

One should note that the anti-flocking algorithm proposed here keeps recalculating the positions of γ-agents as explained in Section III-A. The re-positioning of γ-agents may inject potential energy into the system. Thus, if the total energy of the system exceeds κ_p, according to *Theorem* 1, it can result in collisions among the agents. However, in such a distributed anti-flocking system, it is quite difficult for an α-agent to calculate the instantaneous energy of the system unless the networked system is fully connected.

Secondly, we want to show that the proposed anti-flocking control protocol can steer α-agents to their selfishness goals which are selected such that the networked system can achieve maximum area coverage quickly. In order to do that, we use certain properties of the system in following analyses.

Definition 1 (Permanent block): An α-agent i steered by control protocol (8) is said to be permanently blocked at time

$t > 0$ if both $p_i(t_1) = 0$ and $u_i(t_1) = 0$ for any time $t_1 \in [t, \infty)$.

Lemma 2: Consider an α-agent i steered by the control protocol given in Eq. (8) and its q_i^γ is selected according to Section III-A. Then, α-agent i cannot be permanently blocked.

Based on the above lemma, we come up with following theorem which helps to provide the performance guarantee on the coverage.

Theorem 2: Consider an α-agent i steered by the control protocol given in Eq. (8). If $x \in \widetilde{X}_i$ is selected as the position of its γ-agent at time $t_1 > 0$ according to Eq. (11), i.e. $q_i^\gamma(t_1 + 1) = x$, then x is guaranteed to be covered by an α agent at time $t_2 > t_1$.

In accordance with the above theorem, we can conclude that the proposed anti-flocking algorithm can steer α-agents to achieve their selfishness goals. As explained in Section III-A, selfishness goals are selected such that least recently visited areas get a higher priority. Therefore, the proposed anti-flocking algorithm can achieve dynamic area coverage of an AoI efficiently.

IV. Anti-Flocking with Obstacle Avoidance

In Section III, we have proposed an anti-flocking algorithm for MSNs operate in obstacle free environments. However, most of the MSNs are deployed in remote outdoor environment which are usually populated with obstacles. Therefore, in this section, we propose another algorithm for anti-flocking with obstacle avoidance as an extension to the previously proposed algorithm. Formulations of this algorithm are also partially inspired by Olfati-Saber's flocking algorithms [21]. In our study, we only consider two-dimensional static obstacles that are connected convex regions with smooth edges. We assume that the obstacle locations are known to all α-agents before starting an operation.

We represent obstacles using a set of virtual agents called β-agents. A set of all β-agents are denoted as $\mathcal{V}_\beta = \{1', 2', \ldots, N'\}$. They are another type of static agents which lie on the surface of each obstacle in the environment. The calculation of the position of β-agents is described later in this section. A set of *β-neighbors* of α-agent $i \in \mathcal{V}_\alpha$ at time t is denoted as

$$\mathcal{N}_i^\beta(t) = \{k : k \in \mathcal{V}_\beta, \|q_k^\beta - q_i\| < d_\beta\},$$

where q_k^β is the position of β-agent k and d_β is a positive constant. Neighboring relations between α- and β-agents are represented by using a set of edges $\mathcal{E}_{\alpha,\beta}(t) \subseteq \mathcal{V}_\alpha \times \mathcal{V}_\beta$ which can be given by $\mathcal{E}_{\alpha,\beta}(t) = \{(i,k) : i \in \mathcal{V}_\alpha(t), k \in \mathcal{N}_i^\beta(t)\}$. Since β-agents cannot communicate among themselves, there are no edges among them.

The control input of α-agent i in this algorithm consists of three terms

$$u_i = f_i^d + f_i^s + f_i^c. \tag{15}$$

Here, f_i^d and f_i^s hold the same definitions and implementations as in free-space anti-flocking algorithm while f^c is a newly added term for obstacle collision avoidance. In this work, collision avoidance among α-agent i and its β-neighbors is achieved using a virtual potential field by defining f_i^c as

$$f_i^c = h_i \bar{f}_i^c \text{ and } \bar{f}_i^c = -\nabla_{q_i} V_i^\beta(q). \tag{16}$$

Here, $V_i^\beta(q)$ is a collective potential function based on the relative distance between α-agent i and its β-neighbors. It can be defined using the repulsive pairwise potential function in Eq. (2) as

$$V_i^\beta(q) = \sum_{k \in \mathcal{N}_i^\beta} \psi(\|q_k^\beta - q_i\|, d_\beta), \tag{17}$$

where d_β ($0 < d_\beta \leq r_s$) is the minimum desired distance between α- and β-agents. Selecting $d_\beta > r_s$ may result in coverage holes around to the obstacle boundaries.

In Eq. (16), h_i is a binary function which determines when to repel α-agents from their β-neighbors. In practice, this repulsion should take place only when a mobile sensor nodes is moving towards an obstacle. Otherwise, it may lead to an oscillatory behavior of an α-agent moving toward an obstacle boundary when its corresponding γ-agent locates on the opposite side of the obstacle. In order to avoid such undesirable behavior of α-agents, we define $h_i(t)$ as follows

$$h_i(t) = \begin{cases} 1, & \text{if } \cos^{-1}\left(\frac{\bar{f}_i^c(t) \cdot p_i(t)}{\|\bar{f}_i^c(t)\| \|p_i(t)\|}\right) > \pi/2, \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

According to Eq. (18), there is no repulsion takes place between an α-agent and its β-neighbors while it is moving parallel to the obstacle boundary or away from it.

A. Calculation of Position of β-agents

Since we assume that the locations of all static obstacles are known to α-agents before the start of the operation, their local information maps can be updated to represent the obstructed regions in the AoI. If a cell in the information map coincide with an obstacle in the AoI, that cell should be made unavailable in the calculation of γ-agents's position. Once an α-agent updates its local information map with the available obstacle information, it positions an β-agent at the center of each obstructed cell. Hence the positions of the β-agents can be calculated as the center coordinates of the obstructed cells in the information maps. Repulsion forces on α-agents are activated only when they are within a range of d_β from β-agents. If the width of a cell exceed d_β, α-agents may collide with obstacles before being repulsed. In fact, higher resolution information maps result in more desirable performances in obstacle avoidance since they allow obstacle information to be embedded more precisely.

B. Analysis of Anti-Flocking with Obstacle Avoidance

Apart from the objectives achieved by the free-space anti-flocking algorithm, the algorithm proposed in this section addresses the collision avoidance with obstacles, one of the critical issues in the navigation of mobile platforms. In order to analyze the collision avoidance capability provided by the proposed algorithm, the same technique is adopted as in Section III-B.

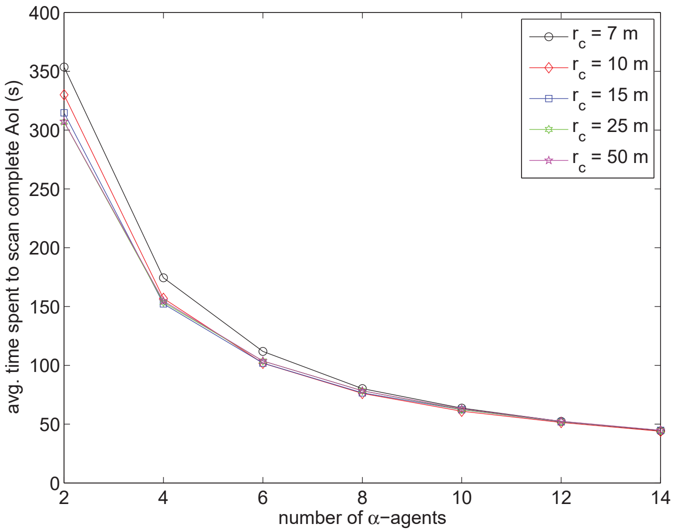

Fig. 2. Average time spent by α-agents that are controlled under the proposed free-space anti-flocking algorithm as a function of number of α-agents. All data points presented are the results of averaging over 1000 realizations.

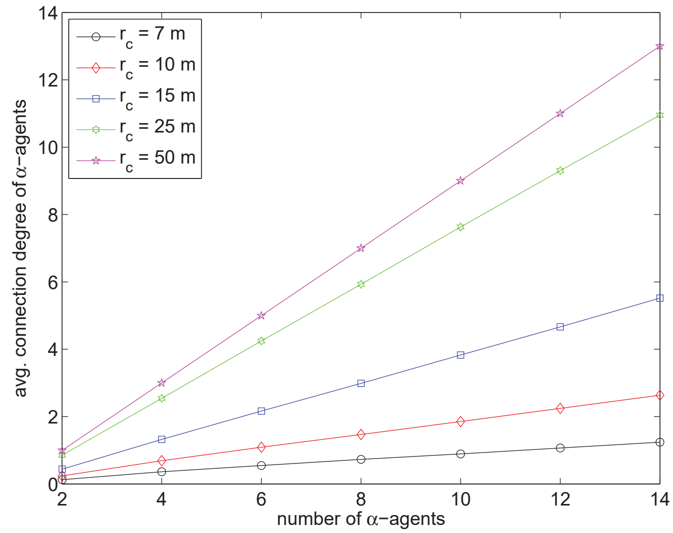

Fig. 3. Average connection degree of α-agents that are controlled under the proposed free-space anti-flocking algorithm as a function of number of α-agents. All data points presented are the results of averaging over 1000 realizations.

We define an energy function for a group of α-, β-, and γ-agents that are applying control protocol given in Eq. (15) as the sum of their potential energy and kinetic energy as given in Eq. (12). The kinetic energy remains the as same as in Eq. (14) and the potential energy of α-agent i can be given as

$$U_i(q) = V_i^{\alpha}(q) + h_i V_i^{\beta}(q) + \kappa_s (q_i - q_i^{\gamma})^{\mathrm{T}} (q_i - q_i^{\gamma}). \quad (19)$$

Lemma 3: The energy $Q(p,q)$ of a group of α-, β-, and γ-agents that are applying control protocol given in Eq. (15), is a non-increasing function of time t for given positions of γ-agents.

Similar to the analysis of free-space anti-flocking algorithm, this non-increasing characteristic of $Q(p,q)$ is used to show that the second anti-flocking algorithm can achieve collision avoidance under certain conditions.

Theorem 3: In a group of N α-agents under the control of protocol given in Eq. (15), α-agents or distinct pairs of α- and β-agents do not collide with each other at any given time $t > 0$ if the initial energy of the system is less than κ_p for given positions of γ-agents.

Since β-agents are static in nature and their positions are predefined, it is always possible to calculate the potential energy between a given α-agent and its β-neighbors. However, since the positions of γ-agents are calculated dynamically, it is quite difficult for an α-agent to calculate the total instantaneous energy of the system unless the networked system is fully connected.

V. Results

In order to analyze the proposed anti-flocking algorithms, we carried out several sets of simulations and the corresponding results are presented in this section. Throughout all the simulations, the cell resolution and update frequency of information maps were fixed to 0.5 m and 10 Hz, respectively. For all algorithms under test, including previous work, the initial positions of α-agents were selected uniformly at random within a given AoI; initial velocities of α-agents were selected uniformly at random from the box $[-1,1]^2$ ms^{-1}. Other parameters of the algorithms are specified separately with each simulation. All the simulations were conducted using MATLAB software on a computer with a 2.67 GHz Intel i7 processor, 12GB memory, and Windows 7 operating system.

A. Free-Space Anti-Flocking

First, we performed a set of simulations to analyze the time spent by MSNs that are controlled under the proposed free-space anti-flocking algorithm to completely scan an AoI with different number of α-agents selected from $N \in [2, 14]$. Here, AoI is a square shaped region with dimensions of 30×30 m^2. The communication range r_c was varied within a range of $[7, 50]$ m in different simulations. Assuming that α-agents stay inside a given AoI throughout a simulation, $r_c = 50$ guarantees a fully connected network because $50 > 30\sqrt{2}$. For a fair comparison, following parameters remained fixed throughout all simulations: $r_s = 3$ m, $d_\alpha = 1.8 r_s$, $\kappa_p = 15$, $\kappa_s = 0.1$, $\kappa_v = 0.6$, $\rho = 0.2$, $\sigma_1 = 0.04$, and $\sigma_2 = 0.01$. Simulation results are given in Fig. 2.

According to the simulation results, it is obvious that the average time spent to scan the complete AoI exponentially decays as the number of α-agents increases for all the values of r_c considered. Hence, the coverage time performances can be considerably improved by slightly increasing the network size. However, the amount of the gain reduces and network infrastructure cost increases as the network size grows. Hence, the network size should be carefully decided to have a good return of investments. Also the gain of coverage time by increasing r_c is minimal for large network sizes, and interestingly, a majority of setups for a given network size reports similar average coverage time despite of their communication range. In order to further analyze these results, we make use of information related to the average connection degree of α-agents in each set of simulations that are presented in Fig. 3.

The average connection degree of α-agents linearly increases with the network size, and unsurprisingly, a network

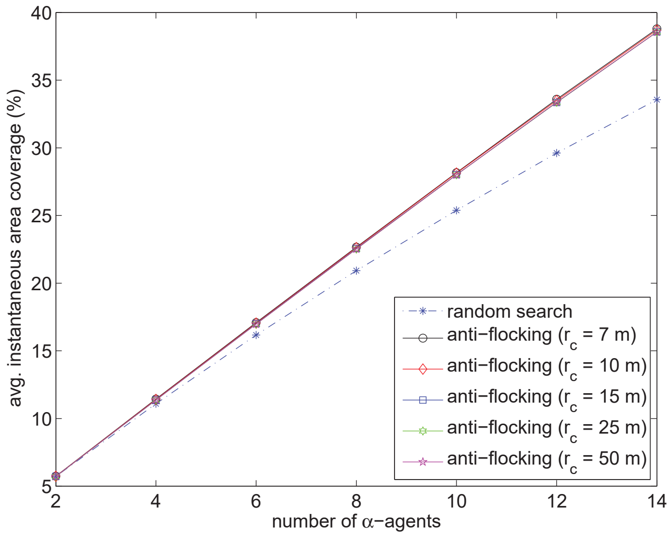

Fig. 4. Average instantaneous area coverage of α-agents that are controlled under the proposed free-space anti-flocking algorithm and random motion model, as a function of number of α-agents. All data points presented are the results of averaging over 1000 realizations.

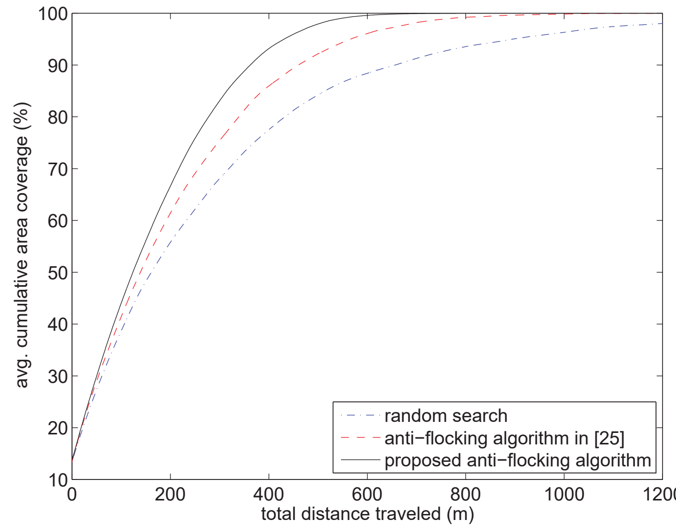

Fig. 5. Average cumulative area coverage of α-agents that are controlled under three different algorithms as a function of total distance traveled by α-agents. All estimates are the results of averaging over 100 realizations.

is fully connected despite of its size when $r_c = 50$ m. Nevertheless, for a fixed network size, the average time spent to scan the complete AoI does not report a considerable reduction as the connection degree increases. According to the results given in Fig. 3, a majority of setups reports minimum average of 1 connection degree throughout a simulation and the average time spent to scan the complete AoI in each of such setups nearly coincide with each other in Fig. 2. When an α-agent gets connected to another α-agent in a network, the first α-agent can access not only the sensing history of second α-agent, but the sensing history of other α-agents in the network that got connected to the second α-agent previously. Therefore, every α-agent in a network need not to connected to every other α-agents in the network to minimize the overlapping of sensing coverage. Based on these observations, we can draw an inference that MSNs with locally interacting sensor nodes can perform equivalently well as MSNs that utilize long range communication modules, under the control of proposed anti-flocking algorithm.

The next set of simulations were performed with the same parameters to analyze the instantaneous area coverage of MSNs that are steered by the proposed anti-flocking algorithm. The instantaneous area coverage of a MSN operating in a given AoI is defined as the probability of a location in the AoI to be covered by at least one sensor at time t [19]. It can also be interpreted as the fraction of area covered by one or more sensors at time t. In order to compare the results of the proposed anti-flocking algorithm, we performed another set of simulations using the random motion model as in [19]. Results of the simulations are given in Fig. 4. According to the given results, the instantaneous area coverage of MSNs that are controlled under the proposed anti-flocking algorithm linearly increases with number of α-agents. It is quite understandable as the instantaneous area coverage is mainly governed by the de-centering term of the anti-flocking algorithm. Nevertheless, the instantaneous area coverage of the MSNs that are controlled under random motion model lag behind the ones under anti-flocking control for any given number of sensor nodes and the difference in instantaneous area coverage increases with the number of nodes. It is mainly due to the increased overlapping of sensing coverage as the mobile sensor nodes are moving randomly.

The third set of simulations were carried out to compare performances of cumulative area coverage of MSNs controlled under the proposed free-space anti-flocking algorithm with a most recently proposed anti-flocking algorithm [25] and a random search model [19]. The simulations were performed on a square shaped AoI with dimensions of 50×50 m^2 using 5 α-agents with $r_s = 5$ m and $r_c = 15$ m. Parameters of the proposed anti-flocking algorithm remained unchanged from previous simulations. Parameters of the anti-flocking algorithm proposed in [25] remained unchanged from their original values. Results of the simulations are given in Fig. 5.

Since the algorithms under test use different velocity models, the cumulative area coverage cannot be compared against search time. For a meaningful comparison, they are compared against the total traveled distance of α-agents that are controlled under each algorithm. Here, we define the cumulative area coverage as the probability of a location in the AoI is covered by at least one sensor for a given total travel distance of α-agents in a network. It can also be interpreted as the fraction of area covered by one or more sensors for a given total traveled distance of α-agents in the network. According to the simulation results given in Fig. 5, the proposed anti-flocking algorithm can steer α-agents to cover a larger area while traveling the same distance as α-agents controlled under other algorithms. Therefore, the proposed algorithm can provide better dynamic area coverage performances.

B. Anti-Flocking with Obstacle Avoidance

The final set of simulations were performed to demonstrate the obstacle avoidance capability of the second anti-flocking algorithm proposed in this paper. The simulations were carried

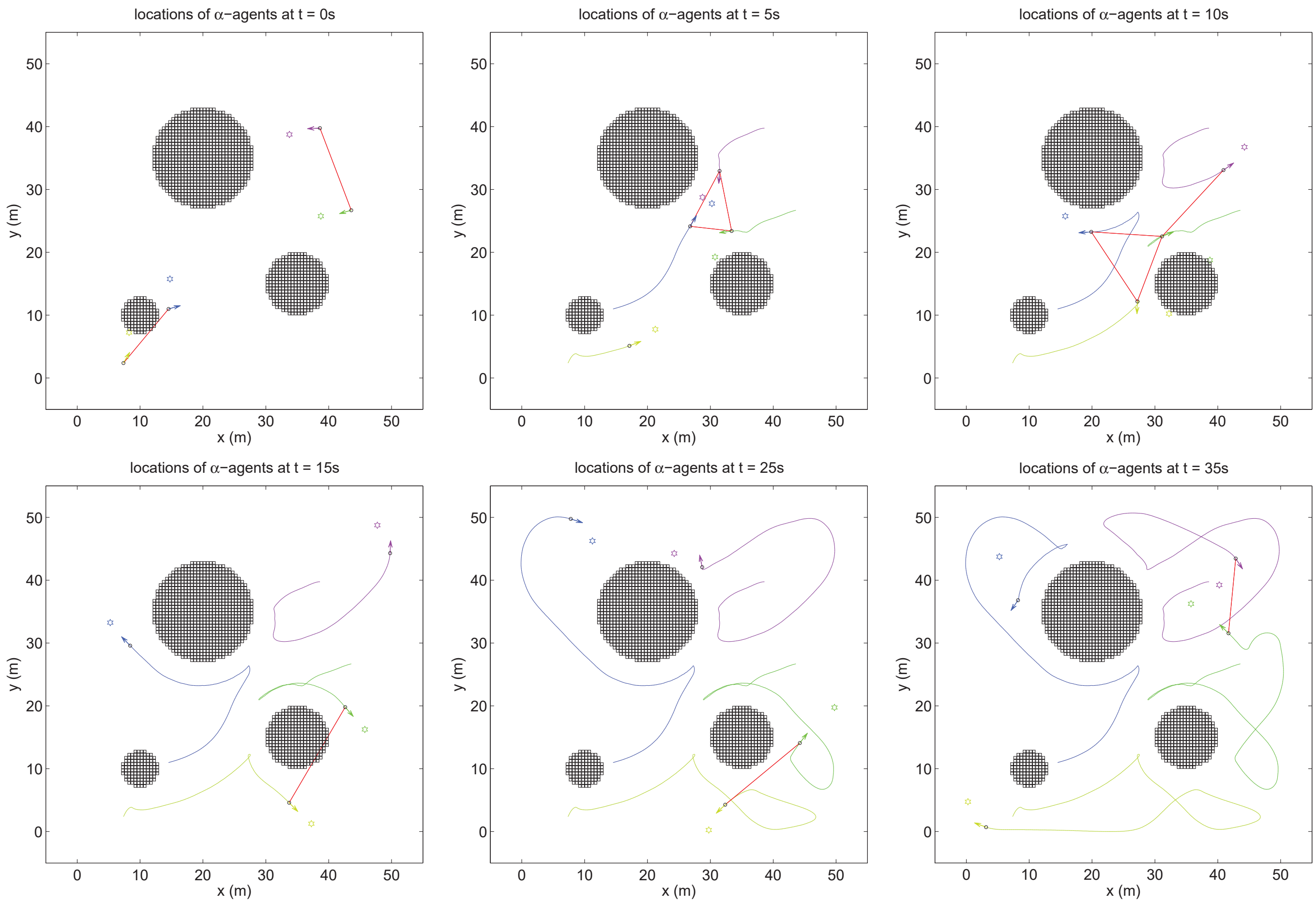

Fig. 6. An illustration of obstacle avoidance capability of the proposed anti-flocking algorithm.

out on a square shaped region with dimensions of 50×50 m^2 with 4 α-agents with $r_s = 5$ m and $r_c = 20$ m. Three circular shaped obstacles with radii of 3 m, 5 m, and 8 m are centered at $(10, 10)$ m, $(35, 15)$ m, and $(20, 35)$ m, respectively. Parameters of the anti-flocking algorithm are selected as follows: $d_\alpha = 1.9 r_s$, $d_\beta = 0.9 r_s$, $\kappa_p = 10$, $\kappa_s = 0.5$, $\kappa_v = 0.8$, $\rho = 0.2$, $\sigma_1 = 0.04$, and $\sigma_2 = 0.01$. Minimum distance between α- and β-agents changes with d_β. One such simulation is illustrated in Fig. 6.

As shown in the first frame ($t = 0$ s), 4 α-agents initiated from random locations within the AoI. Circles, squares, and hexagons denote α-, β- and γ-agents, respectively. A connection between two α-agents are represented by a red colored straight line. As time evolved, they have moved within the AoI according to the control protocol given in Eq. (15). Arrowheads and curved trails represent moving directions and path history of α-agents. As seen from the sample snaps over AoI at several time instants, α-agents had been continuously exploring the AoI while minimizing the overlapping of their sensing coverage. By $t = 35$ s, the MSN has covered a larger portion of the AoI. During the simulations, no collision between α- and β-agents was detected, which demonstrates the obstacle avoidance capability of the second algorithm. Therefore, it can be used with MSNs to achieve dynamic coverage in obstacle dense environments.

VI. Discussions

The results of the simulations presented in the previous section demonstrate the behavior and performance of the proposed anti-flocking algorithms. In this section, we aim to further analyze certain aspects of the proposed algorithms.

A. Parameter Estimation

There are several parameters associated with these algorithms which can be used to tune the behavior of α- and γ-agents. As discussed in Section III-A, the position of a γ-agent is calculated based on the information map using Eqs. (9) and (10). One can identify that there are three parameters, σ_2, σ_1, and ρ, which govern the position of the γ-agent. The parameters σ_1 and σ_2 are respectively used to give higher preferences to locations closer to α-agent and the current location of γ-agent. By selecting target locations closer to their current locations, α-agents can minimize traversal distance during an exploration. The main objective of minimizing the distance between current and next positions of a γ-agent is to attenuate any possible oscillatory behaviors. The parameter $\rho \in (0, 1)$ in Eq. (9) prevents benefit values of remote m_i being attenuated to 0. This ensures that every location in the AoI has an opportunity to be visited by any of the sensor nodes if they have not been visited for a considerable time duration.

The key parameters of the control protocols given in Eqs. (8) and (15) are κ_p, κ_s, and κ_v. Here, κ_p is originally defined in Eq. (2) for the pairwise potential function. It is mainly used to control the distance between α-agents and the distance between α- and β-agents. In *Theorem* 1, it has been proven that α-agents do not collide with each other if the initial energy of the system is less than κ_p for given positions of γ-agents. Hence κ_p should be decided carefully in order to avoid collisions. *Theorem* 3 states a similar condition on collision avoidance between α- and β-agents. Parameters κ_s and κ_v are associated with selfishness terms of the proposed anti-flocking algorithms. Here, κ_s controls the attraction of α-agents towards their γ-agents and κ_v is a damping constant. Having $\kappa_s \gg \kappa_v$ causes α-agents to over accelerate towards their γ-agents which may result in breaking down the motion system of mobile sensor nodes in real world applications. On the other hand, having $\kappa_s \ll \kappa_v$ may slow down the coverage process since α-agents takes longer time to reach their γ-agents. Therefore, a proper balance need to be kept between the values of κ_s and κ_v.

B. Complexity Analysis

In compared with the centralized anti-flocking algorithms, the proposed distributed algorithms can vastly benefit MSNs due to reduced computational and communication overheads. Let i be an α-agent that is controlled by the proposed algorithms and N_n be the number of neighbors of i at any given time $t > 0$, i.e. $|\mathcal{N}_i^\alpha(t)| = N_n$. Then the proposed algorithms keep the communication load of α-agent i within $O(N_n)$ where $0 \leq N_n \leq N$. Computational overheads of the proposed algorithms arise mainly due to the handling of information maps. After each sensor reading, the information maps need to be updated. Let an information map consist of N_c number of cells. Even though not all the cells are updated with each sensor reading, the algorithms first need to identify the relevant cells to be updated, which keeps their computational load within $O(N_c)$. Hence, the computational load of information map sharing with the α-neighbors can be identified as $O(N_n N_c)$. One should note that this quantity changes with the number of α-neighbors and the worst case performance can be given as $O(NN_c)$ which occurs when all other α-agents in the networks lie within the communication radius of i. However, this is extremely unlikely to happen since the α-agents try to be away from each other in order to minimize overlapping coverage.

C. Advantageous of the Proposed Algorithms

Due to fully distributed and intelligent control mechanisms, the proposed anti-flocking algorithms enjoy several advantageous over fully coordinated and random motion models. As demonstrated in the simulation results (Fig. 5), mobile sensor nodes controlled by the proposed anti-flocking algorithms have to travel shorter distances to cover a given AoI compared to those performing random search. Therefore the proposed algorithms can increase the energy-efficiency of MSNs. Even though the objective of the proposed anti-flocking algorithms is to provide better dynamic coverage with smaller number of mobile sensor nodes, the proposed algorithms can also be used with large-scale MSNs. Generally, the number of α-neighbors of a given α-agent are considerably lower compared to the network size and the mobile sensor nodes communicate only with their neighbors. Therefore such MSNs are more scalable compared to fully coordinated MSNs. Furthermore, anti-flocking controlled MSNs can easily adapt to environmental changes since trajectories of the sensor nodes are dynamically obtained according to the up-to-date information. Finally, due to self-organizing behavior of the anti-flocking controlled MSNs, they can work seamlessly in failure of some of nodes or in addition of new nodes. Therefore, anti-flocking controlled MSNs can deliver robust dynamic coverage performances.

D. Limitations and Possible Extensions

The proposed anti-flocking algorithms assume that sensor measurements are noise free. However, actual sensory systems, more often than not, are affected by noise, which might resulted in node localization errors and coverage holes. Therefore, future developments of anti-flocking algorithms should also take sensor noise into consideration. Another limitation of the proposed anti-flocking algorithms is that they ignore communication delays between α-agents. The second anti-flocking algorithm also assume that α-agents can communicate with each other even when they are not in line-of-sight. Such communication aspects are not taken into consideration in the proposed algorithms. Therefore, more realistic communication model may improve the applicability of the anti-flocking algorithms. Finally, obstacle avoidance mechanism used in the second anti-flocking algorithm needs to be generalized to address more complicated scenarios, such as concave shaped dynamic obstacles.

VII. Conclusions

Inspired by the anti-flocking behavior of solitary animals, two emergent motion control algorithms for MSNs are proposed in this paper to achieve efficient dynamic coverage in both obstacle free and obstacle dense environments. In compared with coordinated motion control algorithms, the proposed anti-flocking algorithms provides better scalability, adaptivity, and robustness to MSNs. Due to their self-organizing behavior based on local interactions among neighboring nodes, such MSNs can adapt to the dynamic environments easily. Comparing with random motion models, the proposed anti-flocking algorithms which use distributed information maps, enable MSNs to achieve better performances in both cumulative and instantaneous area coverage by reducing the overlapping in sensing coverage. Results presented in this paper show that the MSNs that are controlled by the proposed anti-flocking algorithms can cover 100% of an AoI by traversing a lesser distance compared to other dynamic coverage algorithms under test. Hence, the proposed algorithms can provide energy-efficient dynamic coverage solutions to mobile surveillance systems utilized in remote and hostile environments.

References

[1] C. Zhu, C. Zheng, L. Shu, and G. Han, “A survey on coverage and connectivity issues in wireless sensor networks,” *Journal of Network and Computer Applications*, vol. 35, no. 2, pp. 619–632, 2012.

[2] R. Falcon, X. Li, and A. Nayak, "Carrier-based focused coverage formation in wireless sensor and robot networks," *IEEE Transactions on Automatic Control*, vol. 56, no. 10, pp. 2406–2417, 2011.
[3] I. Butun, S. D. Morgera, and R. Sankar, "A survey of intrusion detection systems in wireless sensor networks," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 1, pp. 266–282, 2014.
[4] S. He, J. Chen, P. Cheng, Y. J. Gu, T. He, and Y. Sun, "Maintaining quality of sensing with actors in wireless sensor networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 23, no. 9, pp. 1657–1667, 2012.
[5] X. Li, H. Frey, N. Santoro, and I. Stojmenovic, "Strictly localized sensor self-deployment for optimal focused coverage," *IEEE Transactions on Mobile Computing*, vol. 10, no. 11, pp. 1520–1533, 2011.
[6] D. O. Popa, H. E. Stephanou, C. Helm, and A. C. Sanderson, "Robotic deployment of sensor networks using potential fields," in *2004 IEEE International Conference on Robotics and Automation (ICRA)*, vol. 1. IEEE, 2004, pp. 642–647.
[7] J. Chen, S. Li, and Y. Sun, "Novel deployment schemes for mobile sensor networks," *Sensors*, vol. 7, no. 11, pp. 2907–2919, 2007.
[8] K. Derr and M. Manic, "Wireless Sensor Network Configuration–Part I: Mesh Simplification for Centralized Algorithms," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 3, pp. 1717–1727, 2013.
[9] K. Derr and M. Manic, "Wireless sensor network configuration–part II: adaptive coverage for decentralized algorithms," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 3, pp. 1728–1738, 2013.
[10] H. Mahboubi, J. Habibi, A. G. Aghdam, and K. Sayrafian-Pour, "Distributed deployment strategies for improved coverage in a network of mobile sensors with prioritized sensing field," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 1, pp. 451–461, 2013.
[11] H. Mahboubi, K. Moezzi, A. G. Aghdam, K. Sayrafian-Pour, and V. Marbukh, "Distributed deployment algorithms for improved coverage in a network of wireless mobile sensors," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 1, pp. 163–174, 2014.
[12] T. M. Cheng and A. V. Savkin, "Decentralized control of mobile sensor networks for asymptotically optimal blanket coverage between two boundaries," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 1, pp. 365–376, 2013.
[13] Y.-Q. Miao, A. Khamis, and M. S. Kamel, "Applying anti-flocking model in mobile surveillance systems," in *2010 IEEE International Conference on Autonomous and Intelligent Systems (AIS)*. IEEE, 2010, pp. 1–6.
[14] Q. Wang and J. Huang, "A geometric method for improving coverage in sensor networks," in *2012 IEEE International Conference on Systems and Informatics (ICSAI)*. IEEE, 2012, pp. 1111–1115.
[15] Y.-Q. Miao, A. Khamis, and M. Kamel, "Coordinated motion control of mobile sensors in surveillance systems," in *2009 IEEE International Conference on Signals, Circuits and Systems (SCS)*. IEEE, 2009, pp. 1–6.
[16] S. He, J. Chen, X. Li, X. S. Shen, and Y. Sun, "Mobility and intruder prior information improving the barrier coverage of sparse sensor networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 6, pp. 1268–1282, 2014.
[17] B. Liu, P. Brass, O. Dousse, P. Nain, and D. Towsley, "Mobility improves coverage of sensor networks," in *2005 ACM international symposium on Mobile ad hoc networking and computing*. ACM, 2005, pp. 300–308.
[18] D. W. Gage, "Randomized search strategies with imperfect sensors," in *Optical Tools for Manufacturing and Advanced Automation*. International Society for Optics and Photonics, 1994, pp. 270–279.
[19] B. Liu, O. Dousse, P. Nain, and D. Towsley, "Dynamic coverage of mobile sensor networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 2, pp. 301–311, 2013.
[20] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," *ACM SIGGRAPH Computer Graphics*, vol. 21, no. 4, pp. 25–34, 1987.
[21] R. Olfati-Saber, "Flocking for multi-agent dynamic systems: Algorithms and theory," *IEEE Transactions on Automatic Control*, vol. 51, no. 3, pp. 401–420, 2006.
[22] H. Su, X. Wang, and Z. Lin, "Flocking of multi-agents with a virtual leader," *IEEE Transactions on Automatic Control*, vol. 54, no. 2, pp. 293–307, 2009.
[23] N. Ganganath, C.-T. Cheng, C. K. Tse, and X. Wang, "Cluster-based informed agents selection for flocking with a virtual leader," in *2015 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, May 2015, pp. 2692–2695.
[24] S. H. Semnani and O. A. Basir, "Semi-flocking algorithm for motion control of mobile sensors in large-scale surveillance systems," *IEEE Transactions on Cybernetics*, vol. 45, no. 1, pp. 129–137, Jan 2015.
[25] N. Ganganath, C.-T. Cheng, and C. K. Tse, "Distributed anti-flocking control for mobile surveillance systems," in *2015 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, May 2015, pp. 1726–1729.
[26] N. Ganganath, C.-T. Cheng, and C. K. Tse, "Distributed Anti-Flocking Algorithms for Dynamic Coverage of Mobile Sensor Networks – Appendices," The Hong Kong Polytechnic University, Tech. Rep., Nov 2015, http://www.eie.polyu.edu.hk/%7Ebcheng/Papers/TII-15-1018.APPX.pdf.

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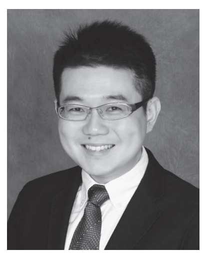

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