Distributed Anti-Flocking Control for Mobile Surveillance Systems

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***Abstract*—Mobile sensor networks (MSNs) are commonly used for monitoring an area of interest (AoI) in security and surveillance systems. Maximizing the area coverage is one of the primary objectives of such systems. With the added mobility over traditional stationary sensor nodes, mobile nodes can adjust their positions inside the AoI to increase the overall coverage. In this paper, we propose an emergent motion control algorithm for MSNs utilized in surveillance applications. The proposed algorithm is inspired by the anti-flocking behaviour of solitary animals. It facilitates robust distributed control for the MSNs to maximize the network coverage. Computer simulations were performed to analyze performances of the proposed algorithm. Simulation results show that under certain conditions, a MSN with the proposed algorithm can achieve similar network coverage as one with centralized anti-flocking control. Furthermore, the proposed distributed control algorithm provides improved scalability and adaptivity over the centralized anti-flocking control and coordinated motion control models.**

***Index Terms*—Mobile sensor networks, surveillance systems, coverage, distributed control, anti-flocking**

I. Introduction

Mobile surveillance systems embrace *mobile sensor networks* (MSNs) which are capable of self-organizing themselves to cope with rapid topology changes. They play an important role in applications where manual deployment of nodes are difficult, such as military applications, environmental monitoring in disaster areas, and real-time monitoring of hazardous materials [1]. The main focus of this paper is devoted to maximize the *network coverage* of MSNs. Even though the coverage problem in stationary sensor networks has been widely studied, only few attempts have been made to improve the coverage of MSNs. Most of the previous work use artificial potential fields [2], [3] or virtual forces [4], [5] to distribute sensors to desired locations in order to achieve an improved network configuration. Although these methods enable MSNs to adapt to a dynamic environment and enhance the network coverage, they cannot guarantee complete coverage of an *area of interest* (AoI) with limited number of nodes.

Dynamic coverage algorithms enable MSNs to monitor relatively large areas with few mobile nodes. Wang et al. proposed a bidding protocol for deploying mobile sensors [6]. Stationary sensors detect the coverage holes locally and bid mobile sensor nodes to move. Mobile nodes receive bids from several stationary nodes and then move to the coverage hole with the highest bid. The sensors move under the influence of such bidding protocol may generate zigzag motion patterns which are highly energy consuming. Miao et al. proposed a coordinated motion control protocol which executes a sweep searching strategy over the AoI [7]. Although coordinated motion control protocols perform well in structured and known environments, they cannot be used in real world surveillance systems which often associated with highly dynamic environments. Furthermore, such protocols are not robust as node failures may occur due to hostilities in the AoI. In contrast to coordinated protocols, random motion control models can be utilized in unknown environments [8], [9]. However, they are not efficient strategies because there is a possibility that one or more nodes may revisit the same area instead of exploring unvisited areas.

Miao et al. proposed an emergent motion control model for maximizing the area coverage of mobile surveillance systems, which is inspired by *solitary behaviours* of some animals [10]. Many social animals show collective behaviours while migrating and foraging, such as birds flocks, fishes schools, and bacteria swarms [11]. In contrast, solitary animals, such as spiders, chipmunks, and tigers, try to be away from each other in everyday search for securing resources like food, water, and space [12], [13]. Solitary foraging strategies of these animals are beneficial to all members of their species in order to maximize their covering area and minimize the overlapping in explored areas. They use different strategies for *territorial marking* and communicating with other individuals. Male tigers mark their territory by spraying urine on trees and marking trails with scat. This high-level cooperation behaviour of solitary animals is called *anti-flocking* behaviour [10].

In [10], Miao et al. introduced the following heuristic rules that governs the dynamics in anti-flocking:

1) Collision avoidance: avoid collisions with others;
2) De-centering: attempt to move apart from neighbours;
3) Selfishness: move to a direction which can maximize own gains.

They used a software-based agent management platform to simulate the anti-flocking behavior for a group of mobile sensor nodes. It outperforms a random motion control model in maximizing the area coverage and is claimed to be more adaptive to the environment compared to coordinated motion control protocols. However, their implementation is based on centralized control which is not desirable for real world mobile sensor networks. In this paper, we introduce a proper mathematical interpretation to the anti-flocking rules proposed by Miao et al. In contrast to the implementation in [10], the proposed algorithm is designed for *distributed control* of MSNs. Therefore, the proposed algorithm is scalable and robust, which make it applicable in many real world applications. Furthermore, we introduce the concept of *information maps* which are inspired by the territorial marking behaviour of solitary animals.

The rest of the paper is organized as follows. In Section II, we revisit some background materials on the topology of mobile sensor networks and introduce the concept of information maps. The novel distributed anti-flocking algorithm is proposed in Section III. Results of our simulation study are presented in Section IV. Concluding remarks are given in Section V.

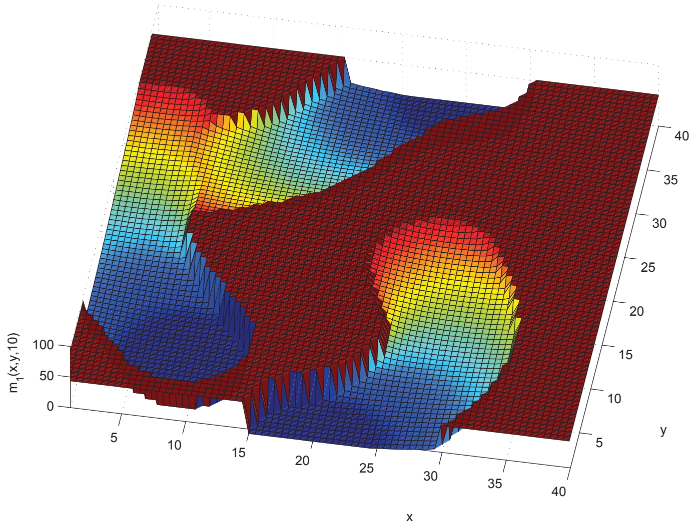


Fig. 1. An illustration of an information map ($N = 3$ and $n = 2$).

II. Preliminaries

A. Topology of Mobile Sensor Networks

We consider a group of N mobile sensor nodes with isotropic radial sensors of range $r_s > 0$. These nodes are moving in n dimensional Euclidean space with double integrator dynamics

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

where $q_i(t), p_i(t), u_i(t) \in \mathbb{R}^n$ are the position, velocity, and control input of the node i at time t. For notational convenience, we often use $q_i(t) = q_i$, $p_i(t) = p_i$ and so on.

We assume identical and isotropic radio communication range/intraction range $r_c (\geq r_s)$ for all the nodes. Hence, *spatial neighbors* of node i at time t can be defined as

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

where $\|\cdot\|$ is the Euclidean norm in $\mathbb{R}^n$. Due to symmetry, $j \in \mathcal{N}_i(t) \Leftrightarrow i \in \mathcal{N}_j(t)$. During the course of motion, $\mathcal{N}_i(t)$ keeps changing with relative distances between nodes. A *dynamic graph of nodes*, $\mathcal{G}(t) = \{\mathcal{V}, \mathcal{E}(t)\}$, can be defined by using a set of vertices $\mathcal{V} = \{1, 2, \ldots, N\}$ whose elements represent the nodes in the group, and a set of edges $\mathcal{E}(t) \subseteq \mathcal{V} \times \mathcal{V}$ such that $(i, j) \in \mathcal{E}(t) \Leftrightarrow i \in \mathcal{N}_j(t)$ which represent the neighboring relations between nodes. Due to the identical interaction range between nodes, $\mathcal{G}(t)$ is undirected, $\forall t > 0$.

B. Information Maps

The node i keeps track of its navigation and sensing history using a local *information map* m_i, which can be represented as a discretized field with similar dimensions to the AoI. Same information map can be used to record the historical data of one's neighbours. First, let us consider the individual updating of m_i. Each cell in m_i at time t is denoted by $m_i(x)$ where x is the center coordinates of the cell and X is a set of all such x values which lie within a given AoI. At $t = 0$, $m_i(x, 0) = \omega (> 0)$, and for all $t > 0$, m_i is updated as

$$m_i(x) = \begin{cases} 0, & \text{if } \|q_i - x\| < r_s, \\ m_i(x, t - \delta t) + \theta \delta t, & \text{otherwise}, \end{cases} \tag{3}$$

where $\frac{1}{\delta t}$ is the sensing frequency and θ is a positive constant.

If $\mathcal{N}_i(t) \neq \emptyset$, node i can exchange its information with node j while $\|q_i - q_j\| < r_c$ and update its own map such that $m_i(x) = \min(m_i(x), m_j(x)), \forall x \in X$ and $\forall j \in \mathcal{N}_i(t)$. Such a fused information map of three nodes moving in 2-dimensional (2D) space at $t = 10$ is illustrated in Fig. 1. In the figure, relatively lower values of $m_1(x, y, 10)$ correspond to recently explored areas in the AoI by one of the sensor nodes, and vice versa.

III. The Proposed Distributed Anti-Flocking Algorithm

In this section, we present a distributed algorithm for anti-flocking in free-space for a group of mobile sensor nodes performing surveillance and monitoring tasks in an AoI. In the proposed algorithm, each node applies a control input that consists of three terms

$$u_i = f_i^c + f_i^d + f_i^s. \tag{4}$$

Each of these terms corresponds to the rules of anti-flocking introduced in [10].

Collision avoidance among nodes is achieved using the term

$$f_i^c = -\nabla_{q_i} V(q), \tag{5}$$

which is inspired by the *gradient-based term* in Olfati-Saber's free-flocking algorithm [14]. For a given configuration of the nodes, $q = [q_1, q_2, \ldots, q_N]^{\mathrm{T}} \in \mathbb{R}^{nN}$, a non-negative smooth collective potential function $V(q)$ is given by

$$V(q) = \sum_{j \in \mathcal{V} \setminus \{i\}} \psi_\alpha(\|q_j - q_i\|_\sigma). \tag{6}$$

For a non-negative parameter ϵ, σ-norm of a vector z is given by $\|z\|_\sigma = \frac{1}{\epsilon}\left(\sqrt{1+\epsilon\|z\|^2}-1\right)$. Note that $\|z\|_\sigma$ is differentiable everywhere whereas $\|z\|$ is not differentiable at $z=0$. The smooth pairwise attractive/repulsive potential function $\psi_\alpha(z)$ is given by

$$\psi_\alpha(z) = \int_{\|d\|_\sigma}^{z} p_h\left(\frac{s}{\|d\|_\sigma}\right)\phi(s-\|d\|_\sigma)ds, \tag{7}$$

where $d(\leq r_c)$ is the minimum desired distance between nodes and $p_h(z)$ can be expressed as

$$p_h(z) = \begin{cases} 1, & \text{if } z \in [0,h), \\ \frac{1}{2}\left[1+cos\left(\pi\frac{z-h}{1-h}\right)\right], & \text{if } z \in [h,1], \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

where $h \in (0,1)$ [14]. In (7), the uneven sigmoidal function $\phi(z)$ is expressed as $(1/2)[(a+b)\sigma_1(z+c)+(a-b)]$, where $0 < a \leq b$, $c = |a-b|/\sqrt{4ab}$, and $\sigma_1(z) = z/\sqrt{1+z^2}$.

The *decentering term* in (4) can be defined as

$$f_i^d = -\sum_{j\in\mathcal{N}_i(t)} a_{ij}(q)(q_j - q_i). \tag{9}$$

For a positive constant λ, terms in the adjacency matrix of graph $\mathcal{G}(t)$ are given by

$$a_{ij}(q) = \begin{cases} \cos\left(\frac{\pi}{2}\frac{\|q_j-q_i\|_\sigma}{\|r_c\|_\sigma}\right)\exp(-\lambda\|q_j-q_i\|_\sigma), \\ \qquad\qquad \text{if } \|q_j-q_i\|_\sigma \leq \|r_c\|_\sigma, \\ 0, \qquad\qquad \text{otherwise.} \end{cases} \tag{10}$$

The *selfishness term* in (4) is aimed to maximize the gain of each sensor node. Our anti-flocking algorithm is designed for mobile sensor networks to maximize their coverage and target detection rate within an AoI. Hence, the selfishness term is aimed to drive each node towards recently unexplored areas close to it. Thus, f_i^s can be defined as

$$f_i^s = -c_1(q_i - q_i^s) - c_2 p_i, \tag{11}$$

where c_1, c_2 are positive constants and q_i^s is the position of an intermediate target of the node i at time t which is selected based on its and its neighbours' exploration history. In order to estimate the position of the intermediate target q_i^s, we define a *benefit function* using $m_i(x)$ such that

$$p_i^b(x) = m_i(x)[\gamma + (1-\gamma)\exp(-\alpha\|q_i - x\| - \beta\|q_i^s - x\|)], \tag{12}$$

where α, β are positive constants. The value of α controls the influence of the spatial gap between a node and its intermediate target while the value of β is used to control possible oscillatory behaviors of the intermediate target as time evolves. A parameter $\gamma \in (0,1)$ prevents remote parts of m_i from attenuating to 0. The intermediate target is decided based on a cell on the local information map of each node, that can maximize $p_i^b(x)$, i.e.

$$q_i^s = \arg\max_{x\in X} p_i^b(x). \tag{13}$$

Using (5), (9), and (11), the control input of the proposed anti-flocking algorithm given in (4) can be summarized as

$$u_i = -\sum_{j\in\mathcal{V}\setminus\{i\}} \nabla_{q_i}\psi_\alpha(\|q_j - q_i\|_\sigma) - \sum_{j\in\mathcal{N}_i(t)} a_{ij}(q)(q_j - q_i) - c_1(q_i - q_i^s) - c_2 p_i. \tag{14}$$

One should note that the control protocol given in (14) assumes different intermediate targets for each node at time t.

IV. Simulation Results

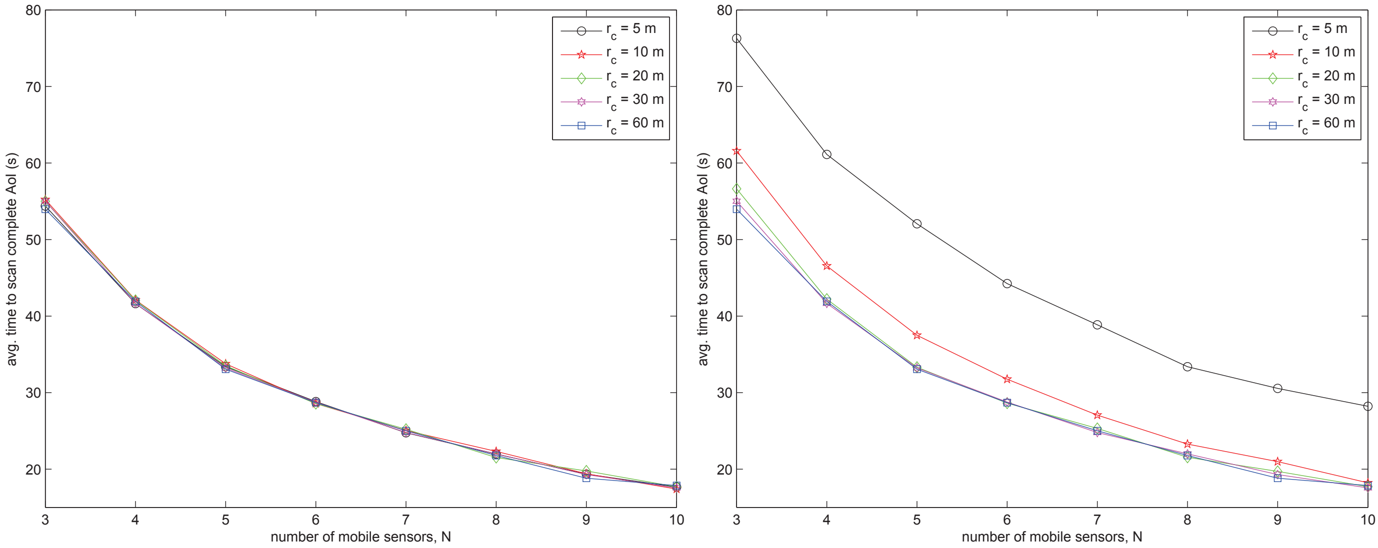
Computer simulations were carried out to evaluate and analyze performances of the proposed distributed anti-flocking algorithm against a centralized anti-flocking algorithm. In centralized anti-flocking, it is assumed that navigation and sensing history of mobile nodes are tracked using a central information map m_c, in contrast to distributed algorithm which assumes every sensor node uses its own local map. Therefore, all the sensor nodes have access to the information of all other nodes in the network $\forall t > 0$. Hence, the benefit function for selecting the next intermediate target for centralized anti-flocking is modified as

$$\tilde{p}_i^b(x) = m_c(x)[\gamma + (1-\gamma)\exp(-\alpha\|q_i - x\| - \beta\|q_i^s - x\|)], \tag{15}$$

which enables sensor nodes to estimate their intermediate goals more accurately compared to the nodes under distributed control.

In simulations, the anti-flocking algorithms under test are provided with an AoI with dimensions of 40×40 m^2. The corresponding information map consists of 80×80 cells. i.e. each cell has dimensions of 0.5×0.5 m^2. Initial positions of the mobile nodes and their intermediate targets were randomly selected within the AoI. Extensive simulations were performed by evaluating the time to scan the AoI completely with $N \in [3, 10]$ number of sensor nodes. For a fair comparison, following parameters were fixed through out all the simulations: $r_s = 5$ m, $d = 5$ m $\epsilon = 0.1$, $a = 1$, $b = 2$, $h = 0.6$, $c_1 = 0.3$, $c_2 = 0.5$, $\alpha = 0.04$, $\beta = 0.01$, $\gamma = 0.2$, $\omega = 1$, $\theta = 5$, and $\lambda = 1$. Initial velocities of the mobile nodes were randomly selected from the box $[-0.01, 0.01] \times [-0.01, 0.01]$ ms^{-1}. Results were obtained by varying $r_c \in [5, 60]$ m ($r_c = 60$ m guarantees a fully connected network because $60 > \sqrt{40 \times 40}$). Simulation results of the two anti-flocking algorithms are given in Fig. 2.

According to the simulation results, the average time spent by the MSN under centralized control to scan the AoI completely is independent of the interaction range (r_c) of sensor nodes. However, they have to use a long range communication module to access to the central information map which carries sensing and navigation history of the other nodes in the network. The MSN under proposed distributed control can achieve exactly the same performances as its centralized counterpart, when the network is fully connected ($r_c = 60$). This is obvious as every node has access to the local maps of every other nodes when they are fully connected. Interestingly,



(a) (b)

Fig. 2. Average time spent by (a) centralized and (b) distributed anti-flocking algorithms to scan the AoI completely as a function of the number of mobile sensors. Simulation parameters are given in Section IV. All data points presented are the results of averaging over 100 realizations.

distributed control can generate very similar performances even for much smaller values of r_c (e.g.: $r_c = 10$ or 20 m). As $r_c \to r_s$, MSNs under distributed control show relatively poor coverage performances as the nodes do not get enough opportunities to interact with their neighbours because of strong repulsion forces. Moreover, the MSNs under distributed control can scan the AoI even faster than their centralized counterparts with slightly higher number of sensor nodes (compare the results of centralized control with $N = 3$ and $r_c = 10$ m against distributed control with $N = 4$ and $r_c = 10$ m in Fig. 2, and so on).

V. Conclusion

A novel distributed anti-flocking algorithm is proposed for maximizing the area coverage of MSNs utilized in surveillance applications. The concept of information maps inspired by territorial marking behaviour of solitary animals, is introduced to minimize the overlap of coverage area of sensor nodes. The proposed distributed control algorithm is scalable, robust, and adaptive to the environment. Simulation results show that under certain conditions, a MSN under the proposed distributed control can achieve similar performances as one with centralized control. It can also compensate the performance gap with MSNs under centralized control by using slightly higher number of sensor nodes. Nevertheless, the operational cost of a sensor node under distributed control is lower as it does not require to access the central information map which is located remotely.

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