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ABSTRACT

Mobile sensor networks (MSNs) are utilized in many sensing applications that require both target seeking and tracking capabilities. Dynamics of mobile agents and the interactions among them introduce new challenges in designing robust cooperative control mechanisms. In this paper, a distributed semiflocking algorithm inspired by *Temnothorax albipennis* migration model is proposed to address the above issues. Mobile agents under the control of the proposed semiflocking algorithm are capable of detecting targets faster and tracking them with lower energy consumption when compared with existing MSN motion control algorithms. Furthermore, the proposed semiflocking algorithm can operate energy-efficiently on both flat and uneven terrains. Simulation results demonstrate that the proposed semiflocking algorithm can provide promising performances in target seeking and tracking applications of MSNs.

Mobile sensor networks (MSNs) can be cost effective tools for detecting and tracking moving targets in outdoor environments. However, there are issues stopping them from being widely adopted in real-world applications, including undesirable sensing performances and high energy consumption due to poor coordinations among mobile agents. This paper introduces a bio-inspired distributed coordination algorithm, which mimics the collective behaviors, known as flocking and antiflocking in animals, and the migration mechanism found in an ant species called *Temnothorax albipennis* (*T. albipennis*). The proposed semiflocking algorithm helps agents to coordinate themselves and to autonomously seek and track targets within the areas of interest (AoIs). Mobile agents under the control of the proposed semiflocking algorithm can efficiently track multiple targets in different terrains under tests. MSNs with the proposed semiflocking can detect and track down targets faster and yield a lower energy consumption due to movements of agents.

I. INTRODUCTION

Mobile sensor networks (MSNs) are highly flexible and scalable, which can be used in a wide range of monitoring applications, such as pursuit-evasion operations, search-rescue missions, and border patrol activities. These typical scenarios require MSNs with effective multitarget seeking and tracking capabilities. It is challenging to search and track multiple moving targets within a finite time in large areas of interests (AoIs).[1] Due to many constraints and uncertainties in real-world applications, such as complex operating environment, changing network topology, and inefficient information exchange, coordinations among mobile agents are seriously affected, thus leading to system instability and unsatisfactory monitoring capability.

There are mainly three technical challenges in this multitarget seeking and tracking problem in complex and rough AoIs. First, in order to control mobile agents to form small groups around each target and avoid having collisions with others, it is necessary to provide suitable interaction regulations and control inputs for each mobile agent.[2] A positive-and-negative consensus model is proposed to describe the attractive and repulsive interactions among agents.[3] Second, an efficient navigation strategy is required to guide mobile agents to improve their target seeking efficiency and reduce their energy consumption. Ganganath *et al.*[4] proposed an energy-efficient navigation strategy for maximizing sensing coverage of MSNs. In their work, the main objective is to inform agents about coverage holes via local information exchanges. However, the antiflocking algorithms can only govern mobile agents to seek the targets instead of continually following them. Third, to guarantee mobile agents to achieve desirable multitarget seeking and tracking performances, a study on the coordination and collaboration among mobile agents is necessary. Noetel *et al.*[5] proposed a pursuit-escape stochastic model for describing the search and return behaviors of mobile agents when they seek for virtual food sources.

Flocking-based algorithms have proven their capabilities in area coverage and target tracking applications.[6,7] In flocking-controlled systems, behaviors of each individual agent are simple but interrelated. These agents are capable of self-organizing via interactions and information exchanges. Thus, complex collective behaviors can be obtained by enforcing simple rules on individual.[8,9] Extensive works on flocking-based algorithms have been focusing on targets seeking and tracking applications in MSNs. Mobile agents track the estimated targets and avoid collisions using a distributed flocking algorithm after the estimation of target locations with a Kalman filter.[10] Jing *et al.*[11] proposed flocking algorithms for mobile agents for tracking multiple targets by forming small groups around each target. Su *et al.*[12] investigated a flocking control and an estimation strategy specifically for two-targets tracking. In their work, mobile agents form a network and then cooperatively estimate target location using a distributed filter. These algorithms mainly focus on the joint problem of target localization and target tracking. However, the efficiency of target seeking has been ignored in their works.

Semnani *et al.*[13] proposed a semiflocking algorithm for searching and tracking multiple targets in MSNs. Based on the distances from an agent to targets and the number of other agents tracking the targets, the agent makes an individual decision on selecting a target to track via a mode switching mechanism. However, this semiflocking algorithm relies on global information of area coverage and target states. The centralized design and the high communication loads limit the practicability and scalability of MSNs. In order to reduce the communication loads in MSNs, event-trigger methods for communications among agents are investigated.[14–16] Event-trigger control is able to optimize the information exchanges process and improve the cooperation efficiency among mobile agents. Yu *et al.* investigated a continuous-time swarm model for multiagent systems considering the limited sensing ranges and the changing communication strategies of mobile agents.[17] Sun *et al.* proposed two pinning control algorithms to reduce the control overheads and enhance the efficiency of communication in complex networks.[18]

Yuan *et al.* proposed a distributed semiflocking algorithm to enable MSNs to seek and track multiple targets in ideal and flat operating environments.[19] In real-world applications, terrain constraints will affect the motion performance of mobile agents, which yield low-efficiency target seeking and tracking. A path planning algorithm has been further incorporated into the target tracking process for mobile agents to avoid obstacles and reach target quickly on rough terrains.[20] However, this method requires priori knowledge of operating terrains (such as terrain fluctuations, vegetation density, and soil characteristics) to construct a mobility map for representing the node speed limits in each subregion.

In order to enhance the multitarget seeking and tracking performance of MSNs on complex terrains, an efficient *Temnothorax albipennis* migration inspired semiflocking algorithm is proposed in this paper. The main contributions of this work are summarized as follows:

1. A distributed semiflocking algorithm inspired by *Temnothorax albipennis* (*T. albipennis*) migration model is proposed for mobile agents to autonomously seek and track targets within the AoI. Mobile agents can adopt a tandem run and a social carrying recruitment strategy to improve their coordinations with other agents and greatly reduce the time required for providing adequate coverage to the targets.
2. A new target selection method is presented. Mobile agents will verify the validity of the targets to avoid tracking invalid targets. Once a target is verified, mobile agents will inform more agents to join and form small groups around the target.
3. The proposed semiflocking algorithm can be applied to MSNs operating in flat or uneven terrains. MSNs under the control of the proposed semiflocking can perform multitarget tracking with short tracking time and low energy consumption.

The rest of this paper is organized as follows. Section II introduces the *T. albipennis* migration model. The proposed *T. albipennis* inspired semiflocking algorithm is presented in Sec. III. Discussion for the energy efficiency performances of the proposed algorithm is provided in Sec. IV. Simulation results and their analyses are given in Sec. V, followed by conclusions in Sec. VI.

II. *Temnothorax albipennis* MIGRATION MODEL

Many social animals exercise collective behaviors on making system-level decisions such as picking food sources or nest locations. Much of these successes depend on their highly self-organized structures, efficient communication mechanisms, and effective division of labor.[21] One successful example of such group-living animals is a rock ant species known as *T. albipennis*.[21,22] Colonies of these ants build nests in rock crevices and frequently emigrate after the deterioration or destruction of their fragile nests.

T. albipennis migration model has been applied in numerous scenarios, such as locations selection, robotics control, behavior teaching, and cooperative learning. In this paper, we consider to incorporate *T. albipennis* migration model into a collaborative targets tracking mechanism for MSNs. Over a migration process, ants share information and cooperate with other nest mates to make collective decisions. A *T. albipennis* migration consists of 6 successive behavioral phases, including individual scouting, food/nest assessment, tandem run recruitment, quorum achievement, social carry recruitment, and migration completion.[21] Initially, scouts individually seek for targets (food sources or nest sites). On finding a potential target, they proceed assessments on this target based on several rules, such as distance between the nest and the target, size of the target, and so on. These scouts can recruit their fellows via slow tandem run recruitment. If there are a certain number of ants (their number is higher than a quorum threshold) around the target and the majority decide to move toward this target, other nest mates are informed via social signals and are carried directly to this target. The migration is completed when there are sufficient number of ants reaching the target.

III. PROPOSED SEMIFLOCKING ALGORITHM

Consider a MSN comprising N mobile agents in a rectangular AoI with width w and length l. The motion of mobile agent i is described by

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

where q_i and p_i are the position and velocity of mobile agent i, respectively, and u_i is the control input of mobile agent i.

A. Motion control on flat terrains

An overview of the proposed semiflocking algorithm is shown in Fig. 1, where n_q is a tuning parameter that represents the quorum threshold, which governs a mobile agent to switch between the artificial tandem run recruitment and social carrying recruitment behaviors. In tandem run recruitment, mobile agents can be informed about the targets via 1-hop or 2-hop communications with their neighbors. On the other hand, mobile agents in social carrying recruitment can be directly informed to move to track the targets. Here, $n_{\max}$ denotes the required number of mobile agents for tracking each target. Furthermore, r_s is the sensing range of a mobile agent and n_k represents the number of mobile agents which are currently tracking a target k.

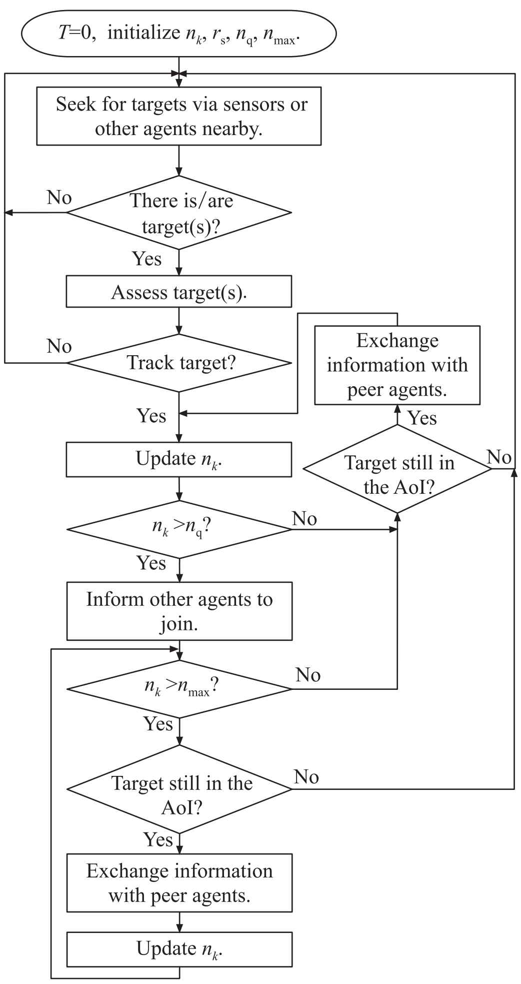

FIG. 1. An overview of the proposed semiflocking algorithm.

Under the proposed semiflocking algorithm, mobile agents are capable of operating in seeking or tracking modes. Initially, all mobile agents operate in seeking mode to scout for new targets within their sensing range. These mobile agents focus on maximizing their area coverage and minimizing their overlapping areas with their fellows. Therefore, each mobile agent in seeking mode applies a control input[13] consisting of three terms as

$$u_i = f_i^g + f_i^d + f_i^s, \tag{2}$$

where the gradient-based term f_i^g[7] is expressed as

$$f_i^g = \sum_{j \in \mathcal{N}_i} \phi_\alpha(\|q_j - q_i\|_\sigma) n_{ij}. \tag{3}$$

Here, q_j is the position of mobile agent j. The vector $n_{ij} = (q_j - q_i)/\sqrt{1 + \varepsilon\|q_j - q_i\|^2}$ is along the line connecting q_i and q_j with $\varepsilon \in (0, 1)$. The action function $\phi_\alpha(x)$[19] is given as

$$\phi_\alpha(x) = \phi(x - d_\alpha)\rho_h\left(\frac{x}{r_\alpha}, h\right), \tag{4}$$

where

$$\phi(y) = \frac{1}{2}\left[(\lambda_1 + \lambda_2)\Gamma(y + \lambda_3) + (\lambda_1 - \lambda_2)\right]. \tag{5}$$

In (4), d_α is a positive constant and $r_\alpha = \|r_c\|_\sigma$, where the σ-norm (i.e., $\|\varphi\|_\sigma$) of a vector is defined as $\|\varphi\|_\sigma = \left[\sqrt{1 + \varepsilon\|\varphi\|^2} - 1\right]/\varepsilon$. Furthermore, r_c is the communication range of all mobile agents. In (5), $\Gamma(\varrho) = \varrho/\sqrt{1 + \varrho^2}$. The parameters λ_1, λ_2, and λ_3 satisfy $0 < \lambda_1 \leq \lambda_2$ and $\lambda_3 = |\lambda_1 - \lambda_2| / \sqrt{4\lambda_1\lambda_2}$.[7] The bump function $\rho_h(\xi, h)$[7] is given as

$$\rho_h(\xi, h) = \begin{cases} 1, & \text{if } \xi \in [0, h), \\ \frac{1}{2}\left[1 + \cos\left(\frac{\pi(\xi - h)}{1 - h}\right)\right], & \text{if } \xi \in [h, 1], \\ 0, & \text{otherwise}, \end{cases} \tag{6}$$

where h is a system tuning parameter and $h \in (0, 1)$.

The velocity consensus term f_i^d[7] is expressed as

$$f_i^d = \sum_{j \in \mathcal{N}_i} (p_j - p_i) a_{ij}(q_i, q_j),$$

with p_j being the velocity of mobile agent j. The spatial adjacency matrix $a_{ij}(q_i, q_j)$[7] is defined as

$$a_{ij}(q_i, q_j) = \rho_h\left(\frac{\|q_j - q_i\|_\sigma}{r_\alpha}\right) \in [0, 1], \quad i \neq j.$$

Furthermore, the selfishness term f_i^s[19] is defined as

$$f_i^s = b_1 \frac{q_i^\eta - q_i}{\|q_i^\eta - q_i\|} - b_2 p_i, \tag{7}$$

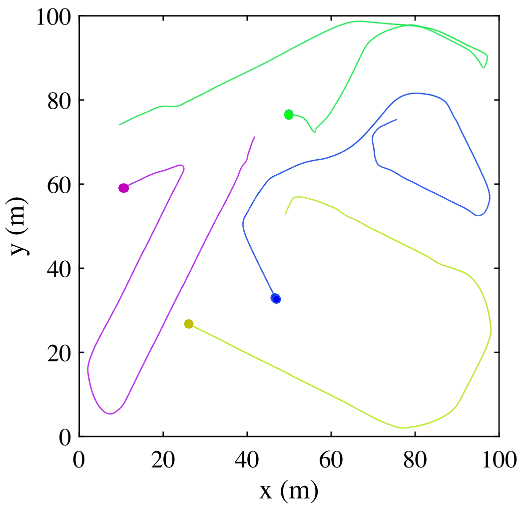

FIG. 2. Trajectories of 4 mobile agents governed by the proposed semiflocking algorithm on a flat terrain. Circles denote mobile agents on the terrain and solid lines represent their trajectories.

where b_1 and b_2 are positive constants. Here, q_i^η is the next searching goal of mobile agent i, which is carefully chosen based on the following mechanism. First, the AoI is divided into many equal-sized patches. A mobile agent records the time that a patch was last visited. A mobile agent can update its record by actually visiting a patch or via information exchange with nearby neighboring agents. Then, among the patches with the longest time not being covered, a mobile agent selects the one with the shortest total distance to both its current position and its current searching goal as the next searching goal q_i^η. All decisions are made based on the available local record of the mobile agent. As illustrated in Fig. 2, mobile agents in seeking mode focus on maximizing their own area coverage while reducing overlaps with others.

Once a target k is detected by mobile agent i within its r_s, it can assess target k based on an evaluation function

$$s_{ik} = \rho_h\left(\frac{n_k}{n_{\max}}, \frac{n_q}{n_{\max}}\right)\rho_h\left(\frac{\|q_k - q_i\|}{l_{\max}}, \frac{r_s}{l_{\max}}\right), \quad (8)$$

where q_k denotes the position of target k and s_{ik} is the assessment result of mobile agent i on target k. Furthermore, $l_{\max}$ is a positive constant with $l_{\max} > r_s$. The function in (8) prioritizes targets that are currently close to mobile agent i and do not have enough tracking mobile agents. Then, mobile agent i gathers the assessment results of different targets. The assessment result s_{ik} will be used as the transition probability for mobile agent i to switch into tracking target k. Based on these transition probabilities, a mobile agent can determine to track a target or remain in seeking mode via a probabilistic decision-making mechanism. If a mobile agent does not detect any target or their target evaluation results are equal to 0, it will continue to seek for new targets. If mobile agent i decides to track target k, it will switch into tracking mode and its control input u_i on a flat terrain is given as

$$u_i = f_i^g + f_i^d + f_i^t, \quad (9)$$

where the target following term f_i^t is defined as

$$f_i^t = b_3(q_k - q_i) + b_4(p_k - p_i).$$

Here, b_3 and b_4 are positive constants and p_k is the velocity of target k.

On the other hand, due to uncertainties in the target detection processes of mobile agents, in this work, a target is verified as a valid target only after it falls under the sensing coverages of n_q mobile agents concurrently. If target k has been discovered by at least one mobile agent and the number of mobile agents currently tracking it is lower than n_q, mobile agents in seeking mode can be recruited through tandem run recruitment. In this tandem recruitment stage, mobile agents in seeking mode will be informed with the information of target k via local communications with those which are tracking it. To avoid imposing too much communication burden onto mobile agents, these mobile agents can only transfer the information of targets via 1-hop or 2-hop communications to their fellows. Those informed mobile agents will then perform their own target assessments using the evaluation function in (8). Based on the evaluation results, they decide to track one of the targets or keep searching for new targets.

If the number of mobile agents that are tracking target k is larger than n_q, it indicates that target k is a valid target. Then, they can attract more mobile agents to directly move toward it through social carrying recruitment. In this social carrying recruitment stage, mobile agents are informed about the information of k via broadcasting. Mobile agents are attracted to track k until the target vanishes or $n_{\max}$ is reached. Under these scenario, mobile agents in the tracking mode will return to the seeking mode.

B. Motion control on uneven terrain

Under conventional semiflocking algorithms, mobile agents (both in the seeking mode and tracking mode) navigate from one location to another using straight paths on a given flat terrain. However, many real-world missions require mobile agents to perform complicated tasks inside uneven terrains. Straight paths on uneven terrains can induce rapid elevation changes which can cause additional expenditure. In order to address this problem, a contour following force is introduced in the proposed semiflocking algorithm to guide mobile agents to move along contours of the uneven terrains. An example of the trajectories of 4 mobile agents governed by the proposed semiflocking algorithm on an uneven terrain is illustrated in Fig. 3.

Consider a mobile agent i moving on an uneven terrain. Let $z(q_i^X, q_i^Y)$ denote the surface elevation of mobile agent i at position $q_i = (q_i^X, q_i^Y)$. The gradient of $z(q_i^X, q_i^Y)$ is a vector pointing at the direction of the greatest increase of $z(q_i^X, q_i^Y)$ and is defined as

$$g(q_i^X, q_i^Y) = \left[\frac{\delta z(q_i^X, q_i^Y)}{\delta q_i^X} \; \frac{\delta z(q_i^X, q_i^Y)}{\delta q_i^Y}\right].$$

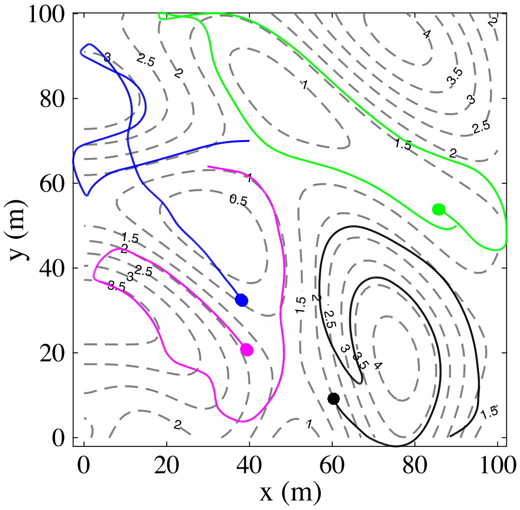

FIG. 3. Trajectories of 4 mobile agents governed by the proposed semiflocking algorithm on an uneven terrain. Circles denote mobile agents on the terrain. Dashed lines and solid lines represent the contours of the terrain and the trajectories of mobile agents, respectively.

The contour following force f_i^{e} is expressed as

$$f_i^{\mathrm{e}} = \begin{cases} -b_5 p_i [g(q_i)]^T \dfrac{g(q_i)}{\|g(q_i)\|}, & \text{if } |g(q_i)\| \neq 0, \\ 0, & \text{otherwise,} \end{cases} \tag{10}$$

with b_5 being a positive constant. In (10), the contour following force is proportional to the negative of mobile agent i's velocity component along the gradient, which discourages the mobile agent from moving up or down contours. Incorporated with f_i^{e}, the control input of mobile agent i moving on an uneven terrain is expressed as

$$u_i = \begin{cases} f_i^{\mathrm{g}} + f_i^{\mathrm{d}} + f_i^{\mathrm{s}} + f_i^{\mathrm{e}}, & \text{mobile agent in seeking mode,} \\ f_i^{\mathrm{g}} + f_i^{\mathrm{d}} + f_i^{\mathrm{t}} + f_i^{\mathrm{e}}, & \text{mobile agent in tracking mode.} \end{cases} \tag{11}$$

With the contour following force, mobile agents are encouraged to move along contours on uneven terrains while scanning the terrain for new targets. As a result, mobile agents under the proposed semiflocking algorithm can reach and track their targets along energy-efficient paths.

IV. DISCUSSION FOR THE ENERGY EFFICIENCY OF THE PROPOSED SEMIFLOCKING ALGORITHM

Consider a MSN governed by the control input in (11) and it has incorporated the *T. albipennis* migration model into its control strategies. On the one hand, mobile agents will verify the validity of targets to avoid tracking invalid targets. On the other hand, mobile agents can utilize the social carrying recruitment strategy to deploy enough mobile agents around valid targets quickly.

Furthermore, according to the properties of MSNs,[4,7] mobile agents which move along terrain contours can save energy compared with those move along the shortest paths between the mobile agents and their corresponding targets.

Based on the above analyses, mobile agents with the *T. albipennis* migration model as explained in Sec. II can provide adequate sensing coverage to targets within AoI quickly. In addition, mobile agents can adopt the energy-efficient navigation method as explained in Sec. III B to further reduce their energy expenditure while traversing within the AoI. Therefore, the proposed semiflocking algorithm can yield lower energy consumption of MSNs.

V. PERFORMANCE EVALUATION

Simulations were conducted to evaluate the performances of the proposed semiflocking algorithm. For all algorithms under test, including existing algorithms,[13,19] their parameters in Table I remain constant. There are 2 randomly moving targets and 24 mobile agents within each terrain under test. The required number of mobile agents for tracking each target was varied from 4 to 10 in different sets of experiments. A set of snapshots in executing the proposed semiflocking algorithm on a $200 \times 200 \times 5\,\mathrm{m}^3$ uneven terrain is illustrated in Fig. 4. According to the results, initially, all mobile agents operated in seeking mode and searched for targets inside flat and uneven terrains. Over time, some mobile agents detected the targets and informed other agents through tandem run recruitment. At a later stage, there were sufficient numbers of the mobile agents (i.e., 4 mobile agents for tracking each target) formed clusters around the targets while other mobile agents remained in seeking mode.

A. Results

The first set of simulations was conducted for comparing the average target tracking time of MSNs with the proposed semiflocking algorithm and the existing algorithms.[13,19] In this paper, "average target tracking time" is calculated as $\sum_{i=1}^{n_{\max}} t_{ik}/n_{\max}$, where t_{ik} is the time when mobile agent i begins to track its target k. The sensing range r_s and communication range r_c of all mobile agents are 10 m and 18 m, respectively. According to the results in Figs. 5(a) and 5(b), the proposed semiflocking algorithm can provide the required coverage to all the targets faster compared to the existing algorithms.[13,19] Mobile agents controlled by the algorithm proposed by Semnani *et al.*[13] navigate based on the visited times of 8 adjacent patches on the terrains. Such an approach can often trap mobile agents in some confined regions and result in relatively low area coverage. Thus, these mobile agents need to spend more time to detect all targets within the terrain. In contrast, mobile agents controlled by the mechanism proposed by

TABLE I. Parameters setting.

Parameters	n_q	ε	λ_1	λ_2	h	b_1	b_2	b_3	b_4	b_5	d_α	$l_{\max}$
Values	3	0.1	5	5	0.2	0.1	0.6	0.05	0.05	0.5	18	100

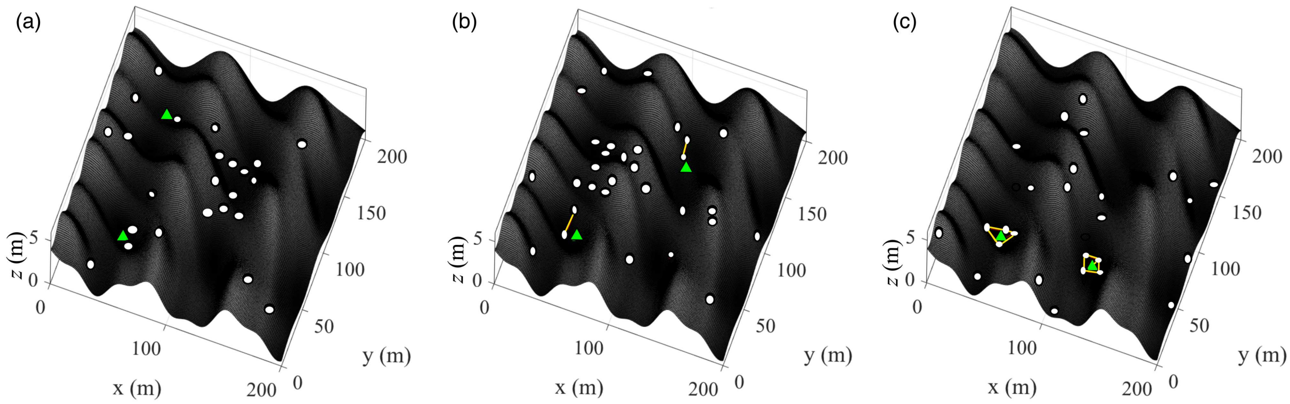

FIG. 4. Snapshots in executing the proposed semiflocking algorithm with 24 mobile agents and 2 targets on an uneven terrains. White circles and green triangles represent mobile agents and targets inside the terrain, respectively. Communication links between mobile agents in tracking mode are denoted by yellow lines.

Yuan *et al.*[19] can effectively visit the coverage holes based on their memories on area coverage and the information exchanged with their neighboring fellows. With such an approach, mobile agents are able to efficiently complete a full scan of the AoI while detect targets more rapidly when compared to the algorithm proposed by Semnani *et al.*[13] For the proposed semiflocking algorithm, similar to the algorithm proposed by Yuan *et al.*,[19] mobile agents can update their memories via their own sensing data or information exchanges with fellow mobile agents. Most importantly, when the number of current mobile agents for tracking a target exceeds n_q, these mobile agents can inform their fellows to quickly reach and track targets via social carrying recruitment. Therefore, the average target tracking time of the proposed semiflocking algorithm is the lowest among the three algorithms and does not significantly increase with the required number of mobile agents for tracking each target.

As illustrated in Figs. 6(a) and 6(b), the proposed semiflocking algorithm has expended much less energy in providing the required coverage to all the targets in both flat and uneven terrains when compared to the existing algorithms.[13,19] With the help of the efficient recruitment strategy and the contour following force, the proposed semiflocking algorithm can reduce energy expenditures by guiding sufficient mobile agents to reach their targets along energy-efficient paths. It is also observed that MSNs under the proposed semiflocking algorithm on flat terrain use shorter target tracking time and lower energy consumption compared to those on uneven terrain. This is because uneven terrain with rapidly changing topographies causes difficulty on controlling mobile agents to go uphill or downhill. Obviously, it also introduces extra energy expenditure of their movements.

The third set of simulations was carried out for comparing the target tracking capabilities of MSNs under the control of the proposed semiflocking algorithm by varying r_s. As illustrated in Figs. 7(a) and 7(b), the target tracking times on both flat and uneven terrains decrease as the sensing ranges of mobile agents increase. It is obvious that mobile agents with longer r_s can sense wider areas when searching their targets. In other words, longer r_s is able to improve the scouting efficiency of mobile agents so that they can detect all targets faster.

The fourth set of simulations was conducted to analyze the target tracking performances of MSNs with the proposed semiflocking algorithm by varying r_c. Based on the results in Figs. 8(a) and 8(b), MSNs with longer r_c can provide the required coverage to all the targets faster on both flat and uneven terrains. It is understandable that mobile agents with longer r_c can exchange information on both area coverage and target tracking with more mobile agents. Thus, mobile

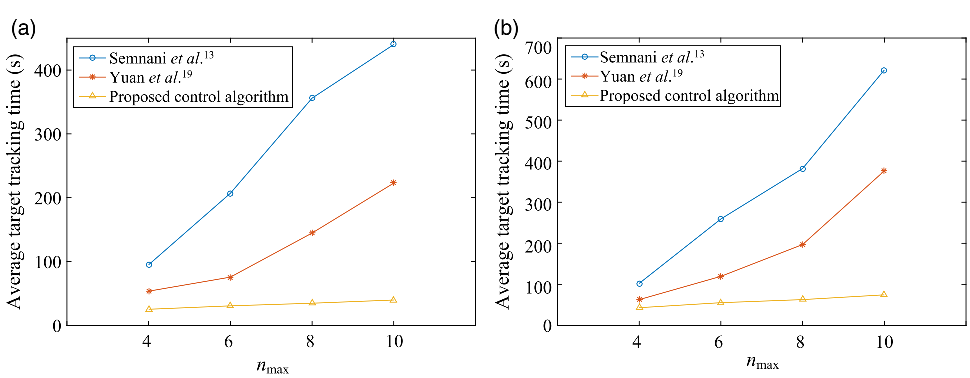

FIG. 5. Average target tracking time of MSNs with different algorithms operating on (a) a flat terrain and (b) an uneven terrain. All data points presented are results of averaging over 100 simulations.

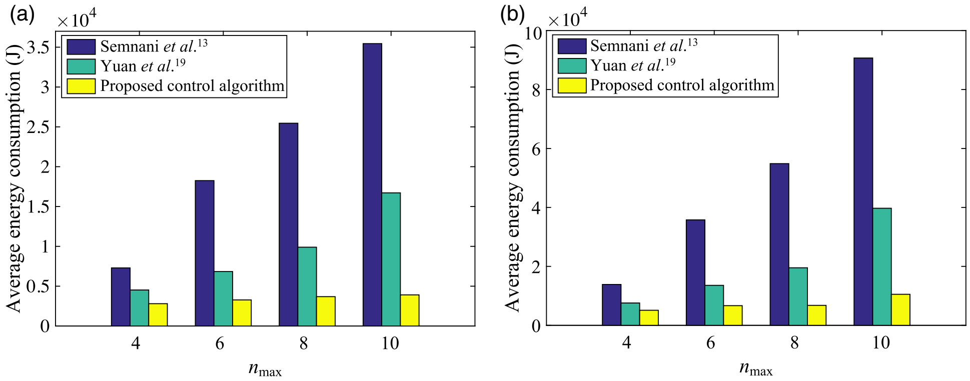

FIG. 6. Average energy consumption of MSNs for tracking all targets on (a) the flat terrain and (b) the uneven terrain. All data points presented are results of averaging over 100 simulations.

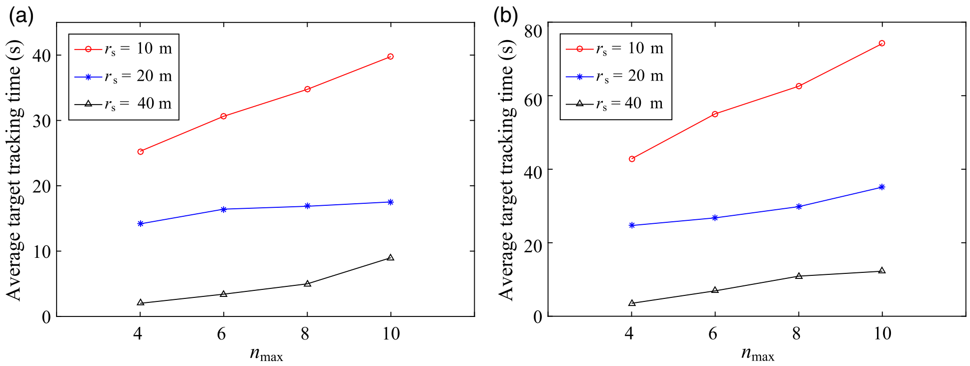

FIG. 7. Average target tracking time of the MSN with different sensing ranges operating on (a) the flat terrain and (b) the uneven terrain. All data points presented are results of averaging over 100 simulations.

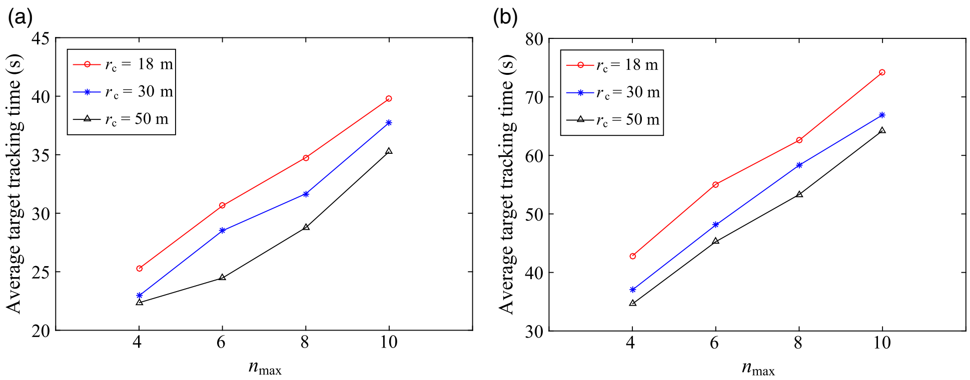

FIG. 8. Average target tracking time of the MSN with different communication ranges operating on (a) the flat terrain and (b) the uneven terrain. All data points presented are results of averaging over 100 simulations.

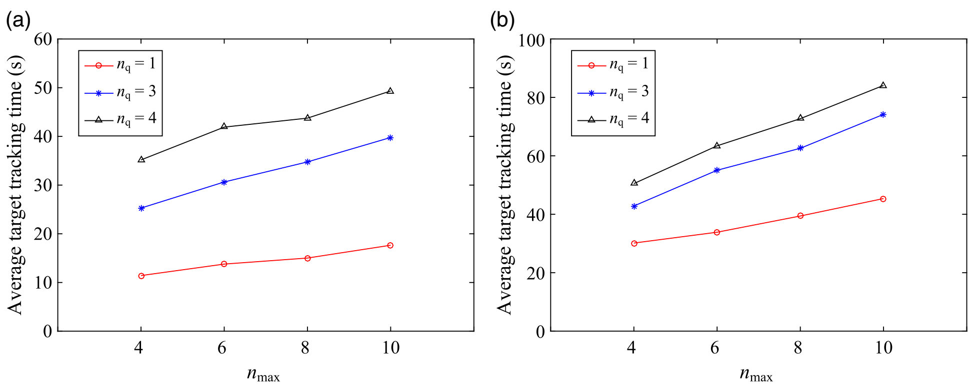

FIG. 9. Average target tracking time of the MSN with different values of n_q operating on (a) the flat terrain and (b) the uneven terrain. All data points presented are results of averaging over 100 simulations.

agents can have a better understanding of their environment and targets within terrains, which enables them to detect targets and attract agents more efficiently.

The last set of simulations was conducted to analyze the target tracking performances of MSNs with the proposed semiflocking algorithm by varying n_q. According to the simulation results in Figs. 9(a) and 9(b), the average target tracking time on both flat and uneven terrains increases with n_q. When $n_q = 1$, once a target is detected by a mobile agent, the information of the target will be broadcasted to other agents without verifications on the validity of the targets. In this case, there is only social carrying recruitment which yields fast target tracking. Thus, MSNs with $n_q = 1$ can track all targets with shortest time. In contrast, when $n_q = n_{max}$, there is only tandem run recruitment. Mobile agents can only inform others about the targets via local communications. In order to balance the tradeoff between target verification and target tracking efficiency, the value of n_q should be carefully chosen according to the specified task requirements and environment constrains.

VI. CONCLUSION

This paper proposed a distributed semiflocking algorithm inspired by the *Temnothorax albipennis* migration model for seeking and tracking targets with MSNs. In order to improve the efficiency and scalability of the MSNs in such applications, mobile agents under the control of the proposed semiflocking algorithm apply effective recruitment strategies and exchange information with their fellows via local communications. A new target selection method is presented to assess targets, and mobile agents decide to track targets or search areas based on such evaluation results. Simulation results verify that MSNs with the proposed semiflocking algorithm can rapidly detect and track targets with low energy consumption on both flat and uneven terrains. Future works will consider the division of labor in MSNs and behaviors learning among mobile agents.

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