The following publication Ganganath, N., Yuan, W., Fernando, T., Iu, H. H., & Cheng, C. T. (2018). Energy-efficient anti-flocking control for mobile sensor networks on uneven terrains. IEEE Transactions on Circuits and Systems II: Express Briefs, 65(12), 2022-2026 is available at 10.1109/TCSII.2018.2822324.

Energy-Efficient Anti-Flocking Control for Mobile Sensor Networks on Uneven Terrains

Nuwan Ganganath, Wanmai Yuan, Tyrone Fernando, Herbert H. C. Iu, and Chi-Tsun Cheng

***Abstract*—Anti-flocking controlled mobile sensor networks (MSNs) have demonstrated impressive dynamic area coverage performances. Even though MSNs are often utilized in outdoor environments that consist of uneven terrains, existing anti-flocking control protocols are designed for flat terrain navigation. Thus they tend to maneuver mobile sensory units along shortest paths between navigation goals in an area of interest. Even though navigating along shortest paths can be both time- and energy-efficient on flat terrains, such motions can often result in excessive energy consumptions on uneven terrains. This paper proposes an energy-efficient anti-flocking control protocol for MSNs based on a terrain adaptation force and a navigation goal selection method. The proposed control protocol encourages mobile sensory units to follow terrain contours whenever feasible. Test results show that the proposed control protocol is a promising energy-efficient solution for MSNs operating on uneven terrains.**

***Index Terms*—Anti-flocking, energy-efficient, distributed motion control, mobile sensor networks, uneven terrains.**

I. Introduction

SURVEILLANCE systems often require manual deployment of stationary sensory units to eliminate coverage holes [1]. Due to the inability of stationary sensory units to self-organize themselves in a given area of interest (AoI), they fail to cope with dynamic changes of the environment. With the added mobility, mobile sensor networks (MSNs) overcome many drawbacks of their stationary counterparts. A mobile sensory unit can increase its coverage by keep moving in a given AoI. A single mobile sensory unit can replace multiple stationary sensory units in providing the same level of sensing coverage. MSNs can start with an arbitrary spatial distribution in the AOI and then self-organize to enchance their global sensory coverage [2], [3]. They can reposition and reorganize themselves in the AoI to take over malfunctioned units or provide on-demand coverages [4]. Due to such advantages of MSNs over their stationary counterparts, they have been continously adopted in outdoor surveillance [5], [6].

Manuscript received January 27, 2018. Accepted for publication March 15, 2018.

This work is supported by the Endeavour Research Fellowship from the Australian Government and the Department of Electronic and Information Engineering, the Hong Kong Polytechnic University (Projects RUWM and G-YBXK).

N. Ganganath, T. Fernando, and H.H.C. Iu are with the School of Electrical, Electronic and Computer Engineering, the University of Western Australia, Crawley, WA, Australia (email: nuwan@ganganath.lk; tyrone.fernando@uwa.edu.au; herbert.iu@uwa.edu.au).

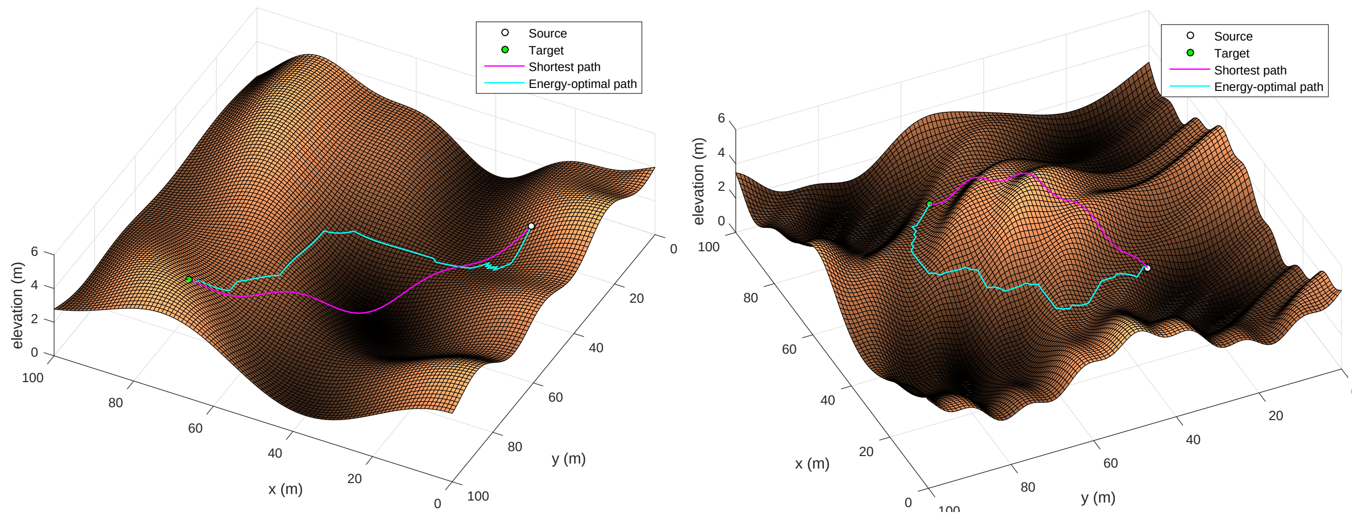
W. Yuan and C.-T. Cheng are with the Dept. of Electronic and Information Engineering, the Hong Kong Polytechnic University, Hung Hom, Koloown, Hong Kong (email: yuanwanmai@gmail.com; chi-tsun.cheng@polyu.edu.hk).

W. Yuan is with the School of Electronics and Information Engineering, the Harbin Institute of Technology, Harbin, Heilongjiang, P.R.China.

Even though MSNs are more versatile compared to stationary sensor networks, their surveillance performances vastly depend on their motion coordination and control mechanisms. Many existing MSN motion coordination and control mechanisms have been based on the fully coordinated controls [5], [7]. However, such control mechanisms restrain the robustness and scalability of MSNs. Fully coordinated controlled MSNs may fail to self-organize themselves to cope with unit additions or removals. Nature-inspired control mechanisms have recently evolved as promising solutions to the above issue. Such mechanisms can be further divided into two categories, namely, flocking control [8]–[10] and anti-flocking control [11]–[13]. Flocking control protocols were inspired by collective behaviors of animals, such as fish schools, bird flocks, and mammal herds [14]. On the other hand, anti-flocking control protocols were inspired by behaviors of solitary animals, such as pumas, spiders, and chipmunks [15].

Anti-flocking control protocols have drawn considerable attention in recent past due to their capability in providing impressive dynamic area coverage for MSNs. In [12], three heuristic rules were introduced to describe the behavior of anti-flocking controlled systems. Mathematical interpretations to those heuristic rules were introduced in [11]. Furthermore, the concept of information maps was first proposed in the same work to achieve fully distributed control of MSNs. In [13], a simplified version of information maps were introduced. The distributed anti-flocking control mecahnism proposed in [13] outperforms dynamic area coverage performances of the previously proposed control protocols [11], [12]. Even though anti-flocking control protocols provide superior adaptability, scalability, and robustness to MSNs, they typically assume a terrain to be flat and ignore physical properties, *e.g.* friction and gravity.

Existing anti-flocking control protocols force a mobile sensory unit to move towards next immediate target along shortest paths. However, shortest paths on uneven terrains often consist of rapid elevation changes, resulting in the use of excessive energy when mobile units move along such paths [16]. Since MSNs are powered by portable energy sources with limited capacity, their operational durations heavily rely on their energy consumption profiles. Energy consumption of MSNs can be reduced by adopting low-power sensors [17], [18]. Energy-efficient control mechanisms may also be applied to further reduce the energy consumption of MSNs. To the best knowledge of the authors, however, these mechanisms have not yet been considered or adopted in MSN dynamic area coverage applications. In order to fill this void, this paper proposes a new distributed anti-flocking algorithm for MSNs which can



(a) (b)

Fig. 1. Samples of shortest and energy-optimal paths on (a) the terrain model 1 and (b) the terrain model 2.

reduce their energy consumption in surveillance applications on uneven terrains.

II. Navigation on Uneven Terrains

The focus of this work is on MSNs utilized in surveillance applications on uneven terrains. Two such terrain models are illustrated in Fig. 1. Note that the shortest paths between the given locations on those terrains consist of bigger elevation changes compared to those energy-optimal paths which tend to follow terrain contours. Even though such path may vary for different mobile units depending on their physical properties, including their mass and the friction coefficient between their wheels and the terrain, traversing contours is generally more energy-efficient as the work to be done against gravity is minimal. This property is used in this work to design energy-efficient anti-flocking control protocol for MSNs. Interested parties may refer to [16] for more details on shortest and energy-optimal path planning on uneven terrains.

Consider a group of mobile sensory units navigating on a terrain. Here, $\tau(x, y)$ denotes the terrain surface elevation of the point (x, y). Let the projection of the position and velocity vectors of a mobile unit i at time t onto the underlying $x-y$ plane are denoted by q_i and p_i, respectively. The gradient vector of $\tau(x, y)$ is given by

$$\gamma(x, y) = \left[\frac{\delta\tau(x, y)}{\delta x} \;\; \frac{\delta\tau(x, y)}{\delta y} \right],$$

which is pointing toward the direction of the highest rate of increase in elevation. The magnitude $\|\gamma(x, y)\|$ is the slope of the terrain in that direction. In order to encourage mobile units to follow the contours, any motion orthogonal to the contours are discouraged by imposing a terrain adaptation force proportional to the negative of the component of p_i along the gradient [19]. The terrain adaptation force for mobile unit i is given by

$$f_i^a = \begin{cases} -\kappa_b p_i [\gamma(q_i)]^{\mathrm{T}} \frac{\gamma(q_i)}{\|\gamma(q_i)\|}, & \text{if } \|\gamma(q_i)\| \neq 0, \\ 0, & \text{otherwise}, \end{cases}$$

where κ_b is a positive constant. Note that $\|\gamma(x, y)\| = 0$ for all (x, y) on flat terrains and for (x, y) that coincide with local minimum or maximum points on uneven terrains. If mobile unit i is already following a contour, p_i and $\gamma(q_i)$ are orthogonal to each other, thus, $p_i[\gamma(q_i)]^{\mathrm{T}} = 0$. That is, the terrain adaptation force is only activated when a mobile unit is deviating from a contour.

III. Energy-Efficient Anti-Flocking Control

This section introduces the proposed energy-efficient anti-flocking control protocol which is based on the terrain adaptation force introduced in the previous section and the anti-flocking algorithm proposed in [13]. Consider an MSN of size N. It is assumed that all N mobile units carry isotropic radial sensors of range $r_s > 0$ and communication modules of range $r_c > 2r_s$. The control input of mobile unit i is given by

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

where f_i^d and f_i^s respectively represent the de-centering and selfishness terms.

In (1), the de-centering term is used to keep mobile units away from each other to maximize instantaneous coverage and avoid collisions. It is defined as

$$f_i^d = -\nabla_{q_i} \left(\sum_{j \in \mathcal{S}_i} \psi(\|q_j - q_i\|, d) \right), \tag{2}$$

where $\mathcal{S}_i = \{j : \|q_j - q_i\| < r_c, j = 1, 2, \ldots, N, j \neq i\}$. In (2), d is the minimum desired distance gap between mobile units and ψ is a non-negative repulsive pairwise potential function [13] which is given by

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

Here, κ_p is a positive constant.

In (1), the selfishness term is used to drive mobile units to visit those recently unexplored areas in the AoI to maximize the cumulative area coverage. It is defined as

$$f_i^s = \kappa_s(r_i - q_i) - \kappa_v p_i, \tag{3}$$

where κ_s and κ_v are positive constants. In (3), r_i is the position of the navigation goal of mobile unit i at time t. The selection of navigation goals have a direct impact on the area coverage performances as they help to guide the mobile units in the AoI. Thus, r_i need to be carefully calculated to improve area coverage performances.

A. Section of Navigation Goals

The proposed anti-flocking control protocol uses information maps [13] to record the sensing history of an AoI. A new navigation goal selection method is introduced to minimize the sensory coverage overlap and to encourage mobile units to follow the contours. It is assumed that each mobile unit carries its own information map. To ease representation, the AoI is first discretized into a set of square cells. Let the center coordinates (x, y) of all cells be denoted by a set W and the local information map of mobile unit i be denoted by m_i. Thereon, $m_i(w)$ carries the information on the time that a cell centred at w was last visited. Initially, $m_i(w) = 0$ for all $w \in W$. As time evolves and the mobile units keep moving in the AoI, $m_i(w)$ is updated as $m_i(w) = t$ if $\|w - q_i\| < r_s$ at time $t > 0$.

Apart from updating local information maps with their sensing history, mobile units exchange their information maps as they communicate with other connected mobile units. Suppose mobile unit i is connected with mobile unit j at time t, *i.e.* $\|q_i - q_j\| < r_c$. Then, mobile unit i receives the local information map of mobile unit j and updates its local information map as $m_i(w) = m_j(w)$ if $m_j(w) > m_i(w)$ for any $w \in W$. Similarly, mobile unit j receives the local information map of mobile unit i and updates its local information map. Such direct exchanges of information maps lead to indirect communication of sensing history among mobile units. Assume mobile unit i connects with mobile unit j and later mobile unit i connects with mobile unit k. Even though mobile unit k has never communicated with mobile unit j before, mobile unit k can receive the slightly delayed sensing history of mobile unit j via the information map from mobile unit i. Such direct and indirect communications lead to efficient information dissemination within an MSN and help in efficient controlling of mobile units.

To calculate r_i, first m_i is evaluated using a benefit function which is given by

$$\varphi_i(m_i, w, t) = (t - m_i(w))(\rho + (1-\rho)\lambda_i(w)), \tag{4}$$

where $0 < \rho < 1$. In (4), $(t - m_i(w))$ is the time span after the cell centered at w has been last covered by sensors of a mobile unit according to the information map m_i at time $t > 0$. In (4), $\lambda_i(w)$ is given as

$$\lambda_i(w) = \exp(-\sigma_1\|q_i - w\| - \sigma_2\|r_i - w\| - \sigma_3\|\tau(q_i) - \tau(w)\|). \tag{5}$$

Here, σ_1 and σ_2 are used to prioritize locations that are close to mobile unit i and its current navigation goal, respectively. In (5), σ_3 is used to give higher preferences to the locations at the same elevation as mobile unit i, *i.e.* to prioritize locations on the same contour as mobile unit i. Mobile units should visit the locations that have the highest benefit values first. Hence, the next navigation goal location is selected as

$$r_i(t+1) = \arg\max_{w \in \widetilde{W}_i} \varphi_i(m_i, w, t),$$

where $\widetilde{W}_i = \{w | w \in W, \|w - q_j\| \geq \|w - q_i\| > r_s, j \in \mathcal{S}_i\}$. The proposed anti-flocking algorithm adopts three recalculation criteria for navigation goals as given in [13].

IV. Performance Evaluations

In this section, the proposed anti-flocking control protocol is analyzed against the anti-flocking control protocol proposed in [13] using the terrain models illustrated in Fig. 1. Mathematical formulations of those terrain models are given in [20]. The energy consumption for navigation during a given time period is calculated as the summation of kinetic energy differences, potential energy differences, and the work done against friction. It is assumed that air resistance is negligible. In all simulations, it is assumed that the mass of a mobile unit is 10 kg, the friction coefficient is 0.01, and gravity is 9.81 ms^{-2}. All simulations were carried out using MATLAB software on a computer with Intel Core i5-6200U CPU, 16GB of RAM, and Microsoft Windows 10.

The simulations were carried out to compare the motion patterns of MSNs controlled by the two anti-flocking control protocols under test. The parameters were set as follows: $r_s = 15$ m, $r_c = 40$ m, $d = 27$ m, $\kappa_b = 10$, $\kappa_p = 15$, $\kappa_v = 0.6$, $\kappa_s = 0.1$, $\sigma_1 = 0.04$, $\sigma_2 = 0.01$, and $\sigma_3 = 0.1$. In the first simulation, three mobile sensory units were distributed uniformly at random on the terrain model 1 and performed monitoring until they achieve 100% cumulative area coverage, *i.e.* a full scan. Motion patterns generated by the mobile units under each control protocols are illustrated in Fig. 2. According to the given results, the mobile units that are controlled by the protocol in [13] tend to move in straight paths where in contrast, mobile units that are controlled by the proposed protocol tend to follow terrain contours. According to the results obtained, the MSN controlled by the protocol in [13] has consumed 3596.63 J in total to complete the full scan. In comparisson, the MSN controlled by the proposed controlled protocol has consumed only 2018.36 J to complete the full scan. In the second simulation, four mobile units were distributed uniformly at random on the terrain model 2 and performed monitoring until they complete a full scan. The corresponding motion patterns are illustrated in Fig. 3. In this simulation, the MSN controlled by the protocol in [13] has consumed 5652.72 J in a full scan. The MSN controlled by the proposed controlled protocol has consumed only 4462.88 J to complete a full scan. According to the results of those two simulations, the proposed protocol leads to more energy-efficient navigation of MSNs over the control protocol in [13].

In order to further verify the above results, extensive simulations were carried out using different numbers of mobile units

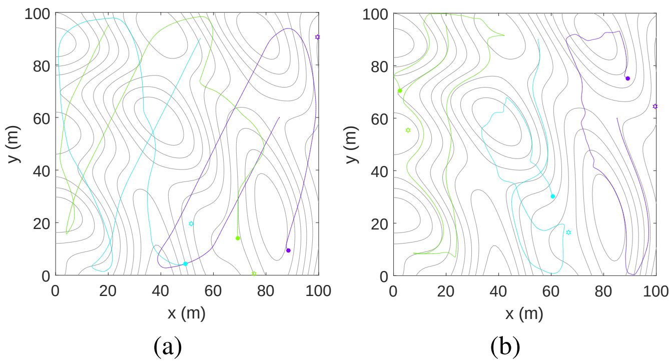


Fig. 2. Motion patterns of 3 mobile units controlled by (a) the anti-flocking control protocol in [13] and (b) the proposed anti-flocking control protocol, on the terrain model 1. Circles and hexagons represent the mobile units and their navigation goals. Curved trails in the same color as the mobile units illustrate their path history. Gray colored lines in the background are contours of the terrain.

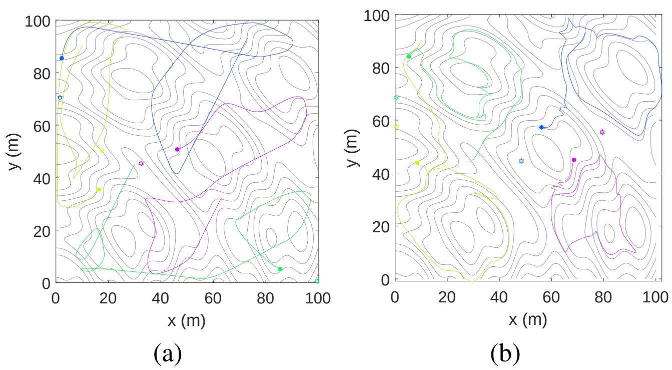


Fig. 3. Motion patterns of 4 mobile units controlled by (a) the anti-flocking control protocol in [13] and (b) the proposed anti-flocking control protocol, on the terrain model 2.

which were innitially distributed uniformly at random on the selected terrains. In all simulations, the following parameters remained fixed for a fair evaluation: $r_s = 10$ m, $r_c = 30$ m, $d = 18$ m, $\kappa_p = 15$, $\kappa_v = 0.6$, $\kappa_s = 0.1$, $\sigma_1 = 0.04$, $\sigma_2 = 0.01$, and $\sigma_3 = 0.1$. Three variations of the proposed control protocol were obtained by setting $\kappa_b = 0$, 5, and 10 correspondingly. Note that the effect of the terrain adaptation force is eliminated by setting $\kappa_b = 0$. Such a setting helps to evaluate the new navigation goal selection method against that in [13].

The first set of simulations were carried out using the terrain model 1. Statistical results of the simulations are given in Fig. 4. According to the results given in Fig. 4a, the instantaneous area coverage of all MSNs under test linearly increases with the network size. It is quite understandable as these anti-flocking control protocols try to minimize the sensory coverage overlaps by keeping mobile units away from each other. Nevertheless, it is obvious that the proposed energy-efficient controls do not affect the instantaneous area coverage of MSNs. According to the results given in Fig. 4b, the proposed navigation goal selection method is able to reduce the energy consumption of mobile units navigating on uneven terrains by prioritizing locations with same elevation as that of the mobile units. Most importantly, the energy consumption of

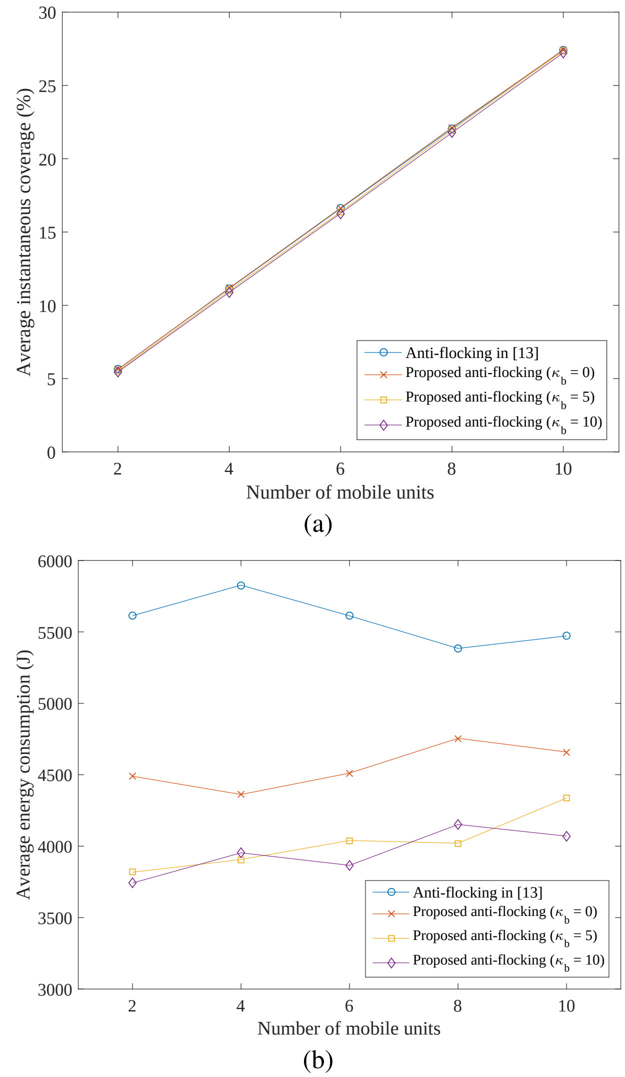


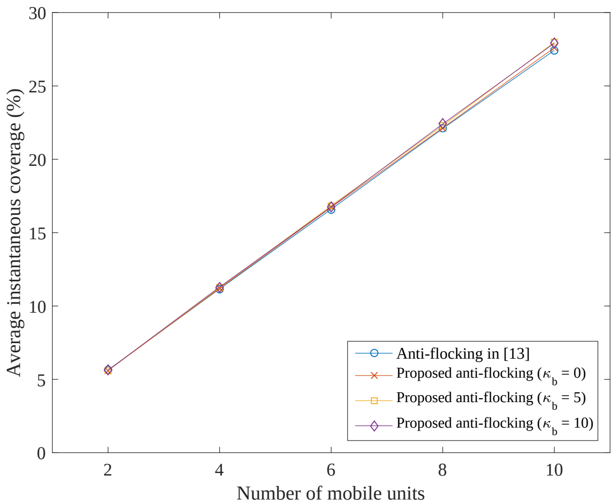
Fig. 4. (a) Average instantaneous area coverage and (b) average energy consumption of MSNs during a full scan of the AoI. All data points have been obtained by averaging results from 50 simulations using the terrain model 1.

mobile units has been further reduced with the introduction of the proposed terrain adaptation force. Interestingly, further increasing the effect of terrain adaptation force by increasing κ_b did not lend further reduction of energy consumption.

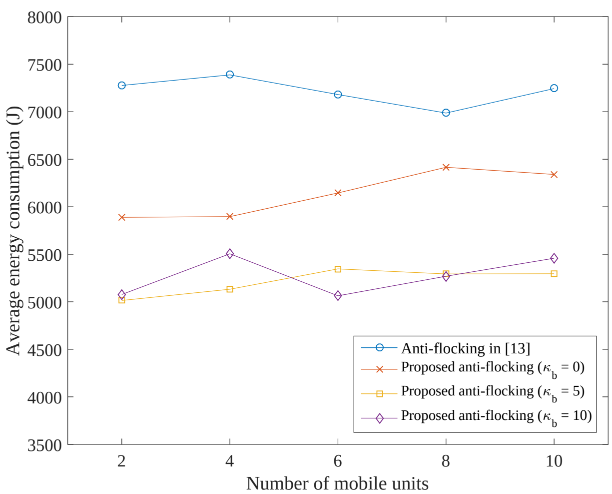
The second set of simulations were carried out using the terrain model 2. Statistical results of the simulations are given in Fig. 5. The given results further confirm the observations made using the results given in Fig. 4.

V. Discussion

According to the simulation results presented in the previous section, the proposed distributed anti-flocking control protocol is capable of minimizing the energy consumption of MSNs utilized on uneven terrains while demonstrating similar dynamic area coverage performances as the anti-flocking control protocol in [13]. However, mobile units may take longer time to explore an environment under the proposed control protocol as they tend to follow terrain contours which usually results in longer paths compared to shortest possible paths.



(a)



(b)

Fig. 5. (a) Average instantaneous area coverage and (b) average energy consumption of MSNs during a full scan of the AoI. All data points have been obtained by averaging results from 50 simulations using the terrain model 2.

Hence, the proposed anti-flocking control protocol is more suitable for applications which energy consumption is given a high priority. This work only focuses on minimizing the energy used for the navigation of mobile units. The energy consumed by mobile units is not only for navigation but also includes communication, sensing, processing, and so on. The minimization of the energy consumption of those additional modules should be addressed separately and it is out of the scope of this work.

VI. Conclusion and Future Work

An energy-efficient anti-flocking control protocol is proposed for MSNs utilized on uneven terrains. A terrain adaptation force is introduced to encourage mobile units to suppress motions that are orthogonal to terrain contours. A navigation goal selection method is proposed to minimize the sensory coverage overlaps and energy consumption by prioritizing locations with the same elevation as that of mobile units. Simulation results demonstrate impressive energy saving capabilities of the proposed anti-flocking protocol.

All existing anti-flocking control protocols, including the proposed protocol, try to keep mobile units moving all the time. It could be possible to save more energy by resting some of the mobile units if a satisfactory dynamic area coverage has been achieved in their surrounding area. Hence, future work should study the effect of stalling mobile units adaptively.

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