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# Energy-Efficient Semi-Flocking Control of Mobile Sensor Networks on Rough Terrains

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***Abstract*—Mobile sensor networks (MSNs) with semi-flocking control protocols have demonstrated promising performances in both area coverage and target tracking. However, they may not operate at their highest efficiencies due to poor utilization of local information and deficient motion coordinations among mobile nodes. In this paper, a distributed semi-flocking control protocol based on local information exchanges is proposed to address the above issues in MSNs. Most existing semi-flocking control protocols are designed for patrolling in flat terrains and maneuvering nodes using shortest paths between two points on the given terrains. Such assumptions and the corresponding decisions do not apply well on real-world rough terrains and they often impose extra energy expenditure to mobile nodes. To address this problem, a terrain adaptation force and a navigation goal selection method are integrated into the proposed control protocol. Our study on rough terrains illustrates that the proposed control protocol is capable of achieving better performances in both area coverage and target tracking with lower energy expenditure when compared to the state-of-the-art flocking-based control protocols.**

***Index Terms*—Semi-flocking, mobile sensor networks, distributed control, energy-efficient, rough terrains.**

## I. Introduction

EQUIPPED with added mobility, mobile sensor networks (MSNs) are capable of relocating and reorganizing themselves to deal with rapidly changing topologies and different mission objectives. Area coverage and target tracking are two key issues which are studied extensively in the field of MSNs [1], [2]. Applications with demands on both area coverage and target tracking are numerous, such as pursuit-evasion problems [3], search-rescue missions [4], and border patrol operations [5]. The main constraint of MSNs is the limited energy available in their mobile nodes [6], [7]. Energy conservation of mobile nodes is critical for prolonging the lifetime of MSNs [8]. However, many existing MSN control protocols overlook such an issue and result in excessive energy consumption.

In recent years, nature-inspired algorithms have attracted enormous attention [9]–[14]. In [9], Khanna *et al.* proposed a reduced-complexity genetic algorithm to provide optimal secure coverage and enhance battery life via dynamic relocatability in MSNs. To assure certain levels of target coverage and network connectivity, Liao *et al.* [11] presented two heuristic algorithms, *i.e.* a clique partition based algorithm and a Voronoi partition algorithm, to shorten motion paths of sensors. In [12] and [13], a nature-inspired control protocol, namely semi-flocking, is introduced to bridge the gap between flocking-control and anti-flocking-control. Flocking control is inspired by the collective behaviours of social animals [15], while anti-flocking control is inspired by the foraging strategies of solitary animals [16], [17]. A flocking algorithm which guarantees the velocities of mobile nodes to reach consensus is presented in [18] that each node is assumed to acquire nonlinear measurements of the relative velocity between itself and its neighboring nodes. While semi-flocking-controlled mobile nodes can allocate part of them to form clusters around targets and let the rest to explore other unknown areas.

Semi-flocking control protocols are promising for tracking multiple targets and monitoring large-scale environment. However, semi-flocking control protocols in [12] and [13] rely on global information regarding the conditions of the mobile nodes and utilize a centralized mode switching mechanism. Such a centralized design hinders their scalability and applicability in practical MSN deployments. Mobile nodes controlled by the semi-flocking control protocols in [12], [13] navigate based on the information of their 8 adjacent areas, which dramatically degrades their area coverage performances. Moreover, existing semi-flocking control protocols assume terrains to be flat and guide mobile nodes to move along shortest trajectories towards their goal positions. However, shortest paths on rough terrains may impose rapid elevation changes which often need excessive energy expenditure [7]. To the best of authors' knowledge, there is no formal investigation on energy-efficient motion control for MSNs that can fulfill the demands on both area coverage and target tracking.

In order to tackle all the aforementioned problems, this paper presents a distributed energy-efficient semi-flocking control protocol for MSNs on rough terrains. The rest of this paper is organized as follows. Section II presents the distributed semi-flocking control protocol. Section III introduces the energy-efficient navigation control protocol for mobile nodes on rough terrains. Simulation results are provided in Section VI, followed by discussions in Section V. Concluding remarks are given in Section VI.

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## II. Distributed Semi-flocking Control Protocol

### A. Motion Control of Mobile Nodes

Consider a MSN consisting of *N* mobile nodes moving in a rectangular region with width *w* and length *l*. The motion of mobile node $i$ is governed by

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

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

Mobile nodes steered by the proposed semi-flocking control protocol can switch their operating modes between flocking and anti-flocking modes. Mobile nodes in flocking mode gather and form clusters around targets. While mobile nodes in anti-flocking mode scatter to search for new targets. The control input $u_i$ of mobile node $i$ [15] is defined as

$$u_i = \begin{cases} f_i^g + f_i^d + f_i^s, & \text{in anti-flocking mode,} \\ f_i^g + f_i^d + f_i^t, & \text{in flocking mode.} \end{cases} \tag{2}$$

Here, $f_i^g$ is a gradient-based term [15] and it is defined as

$$f_i^g = n_{ij}\phi_\alpha(\|q_j - q_i\|_\sigma),$$

where $n_{ij} = (q_j - q_i)/\sqrt{1 + \epsilon\|q_j - q_i\|^2}$. Here, $q_j$ is the position of node $j$ and $\epsilon \in (0, 1)$. Here, $\sigma$-norm of a vector is defined as $\|z\|_\sigma = \left[\sqrt{1 + \epsilon\|z\|^2} - 1\right]/\epsilon$. The action function $\phi_\alpha(z)$ [15] is defined as

$$\phi_\alpha(z) = \phi(z - d_\alpha)\rho_h\left(\frac{z}{r_\alpha}\right), \tag{3}$$

where

$$\phi(z) = \frac{1}{2}\left[(a + b)\sigma_\eta(z + c) + (a - b)\right]. \tag{4}$$

In (3), $r_\alpha = \|r_\mathrm{c}\|_\sigma$ and $r_\mathrm{c}$ is the communication range of each mobile node, and $d_\alpha$ is a constant of $\alpha$-lattice. In (4), $\sigma_\eta(z) = z/\sqrt{1 + z^2}$ is an uneven sigmoidal function. The parameters $a$, $b$, and $c$ satisfy $0 < a \le b$ and $c = \mid a - b \mid /\sqrt{4ab}$ [12]. Furthermore, the bump function $\rho_h(z)$ [15] is expressed as

$$\rho_h(z) = \begin{cases} 1, & \text{if } z \in [0, h), \\ \frac{1}{2}\left[1 + \cos\left(\frac{\pi(z-h)}{1-h}\right)\right], & \text{if } z \in [h, 1], \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where $h \in (0, 1)$.

In (2), the velocity consensus term $f_i^d$ [15] is given as

$$f_i^d = (p_j - p_i)a_{ij}(q_i, q_j),$$

where $p_j$ is the velocity of node $j$, and the spatial adjacency matrix $a_{ij}(q_i, q_j)$ [15] is given as

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

When mobile nodes search for targets, they switch into anti-flocking mode. In (2), the selfishness term is defined as

$$f_i^s = c_1\frac{(q_i^\gamma - q_i)}{\|q_i^\gamma - q_i\|} - c_2 p_i, \tag{6}$$

where $c_1$ and $c_2$ are positive constants, and $q_i^\gamma$ is the navigation goal of mobile node $i$, which is carefully selected in order to increase its area coverage. The navigation goal selection method will be introduced in Section III.

When mobile nodes are tracking targets, they switch into flocking mode. For a mobile node $i$ that is tracking a target $k$ located at $q_k$ with a velocity $p_k$, its group objective term is defined as

$$f_i^t = c_3(q_k - q_i) + c_4(p_k - p_i),$$

where $c_3$ and $c_4$ are positive constants.

### B. Local Information Exchanges

The mode-switching mechanism in the proposed control protocol, which makes decisions based on local information exchanges among mobile nodes, is elaborated in this section.

Mobile node $i$ can receive target $k$'s information, including its identity, location, and velocity via its sensing module or local communications with other mobile nodes. After receiving target $k$'s information, mobile node $i$ will evaluate the fitness of target $k$ using an assessment function

$$\Upsilon_{ik} = \varrho\frac{r_\mathrm{s}}{\|q_k - q_i\|}\Gamma\left(n_{ik}\right). \tag{7}$$

Here, a generic system parameter $\varrho$ is used to incorporate any possible undesirable impacts due to the delay in data transmission. For illustrative purposes, the value of $\varrho$ is arbitrarily chosen as $1$ when a target is within the sensing range of a mobile node, $0.8$ when a mobile node receives information of a target via single-hop communications, and $0.6$ when a mobile node receives target information via 2-hop communications. In practice, values of $\varrho$ should be determined based on the unique properties of the actual system and the targets. Here, $r_\mathrm{s}$ is the sensing range of a mobile node. In (7), $\Gamma\left(n_{ik}\right)$ varies between 0 and 1 and is given as

$$\Gamma\left(n_{ik}\right) = \begin{cases} 1, & \text{if } n_{ik} \in [0, n_{\min}), \\ \frac{1}{2}\left[1 + \cos\left(\frac{\pi(n_{ik} - n_{\min})}{n_{\max} - n_{\min}}\right)\right], & \text{if } n_{ik} \in [n_{\min}, n_{\max}], \\ 0, & \text{otherwise,} \end{cases}$$

where $n_{ik}$ denotes the number of mobile nodes that are currently tracking target $k$. In this work, $n_{ik}$ is obtained via local communications, and thus guarantees the distributed nature of the proposed control protocol. Furthermore, $n_{\max}$ and $n_{\min}$ are system parameters that respectively represent the maximum and the minimum required numbers of mobile nodes for tracking a target.

From (7), the assessment result of mobile node $i$ on target $k$ is high if target $k$ has a low number of tracking nodes and it is in close proximity to mobile node $i$. Conversely, the assessment result is low when the target is far away or it is currently tracked by enough mobile nodes. The design rationale is to achieve desirable trade-offs between area coverage and target tracking. Moreover, it can balance the sizes among tracking clusters. After obtaining assessment results on various targets, they are normalized to calculate the state transition probability of mobile node $i$ as

$$P_{ik} = \frac{\Upsilon_{ik}}{\sum_{\tau=1}^{M}\Upsilon_{i\tau}},$$

**Algorithm 1** The mode switching mechanism for mobile node $i$.

**for** target $k$ = 0 to $M$ **do**<br>
  **if** $\|q_k - q_i\| \le r_\mathrm{s}$ or mobile node $i$ received target $k$'s information via neighboring nodes **then**<br>
    $\Upsilon_{ik} = \varrho \frac{r_\mathrm{s}}{\|q_k - q_i\|} \Gamma(n_{ik})$ ;<br>
  **else**<br>
    $\Upsilon_{ik} = 0$;<br>
  **end if**<br>
**end for**<br>
**for** target $k$ = 0 to $M$ **do**<br>
  **if** $\sum_{\tau=1}^{M} \Upsilon_{i\tau} > 0$ **then**<br>
    $P_{ik} = \frac{\Upsilon_{ik}}{\sum_{\tau=1}^{M} \Upsilon_{i\tau}}$<br>
  **end if**<br>
**end for**<br>
**if** $\sum_{\tau=1}^{M} P_{i\tau} > 0$ **then**<br>
  Select one of the targets to track according to their transition probabilities and switch to flocking mode;<br>
**else**<br>
  Switch to anti-flocking mode.<br>
**end if**

if $\sum_{\tau=1}^{M} \Upsilon_{i\tau} > 0$. Here, $M$ is the total number of targets on the terrain. The normalized result $P_{ik}$ is the transition probability for mobile node $i$ in the anti-flocking mode to switch into tracking target $k$. If mobile node $i$ does not receive any information on the targets or $\sum_{\tau=1}^{K} \Upsilon_{i\tau} = 0$, it will keep searching the area for potential targets. The pseudocode of the mode switching mechanism for mobile node $i$ is given in Algorithm 1.

## III. Energy-Efficient Navigation

This section introduces the energy-efficient navigation control protocol for mobile nodes on rough terrains. When mobile nodes move along their shortest paths toward their navigation goals, frequent ascending and descending movements associated with the paths may result in excessive energy consumption. To avoid mobile nodes from going through paths that are relatively short but require higher energy expenditure due to huge elevation differences, an energy-efficient contour following strategy can be a practical solution [7].

Consider a mobile node $i$ navigating on a rough terrain. Let $h(x,y)$ denote the surface elevation of mobile node $i$ at position $q_i = (x,y)$. The gradient vector of $h(x,y)$ [8] is therefore given by

$$g(x,y) = \left[ \frac{\delta h(x,y)}{\delta x} \, \frac{\delta h(x,y)}{\delta y} \right],$$

which is pointing towards the direction of the gradient of $h(x,y)$ with the steepest ascent. To impel mobile nodes to move along contour lines, a terrain adaptation force is applied to against any motions orthogonal to the contours. The terrain adaptation force [7] for mobile node $i$ is given by

$$f_i^c = \begin{cases} -c_5 p_i [g(q_i)]^T \frac{g(q_i)}{\|g(q_i)\|}, & \text{if} \quad \|g(q_i)\| \neq 0, \\ 0, & \text{otherwise}, \end{cases} \tag{8}$$

where $c_5$ is a positive constant. In (8), the terrain adaptation force is proportional to the negative of node $i$'s velocity component along the gradient. If mobile node $i$ is following the contours, $p_i[g(q_i)]^T = 0$ as $p_i$ is orthogonal to $g(q_i)$. Otherwise, the terrain adaptation force is having a finite value which discourages the mobile node from going uphill or downhill.

In this paper, a new navigation goal selection method is further proposed to maximize the area coverage and to urge mobile nodes to move along contours. The monitoring region is divided into a large number of equal-sized cells. Let $w$ denote the center of a cell and $m_i$ be the information map of mobile node $i$. Each mobile node records its information on the last visiting time of a cell centered at $w$ as $m_i(w)$. Let $W$ be a set of the center coordinates $w$ of all the cells. Initially, $m_i(w) = 0$ for all $w \in W$. As mobile node $i$ keeps moving within the region, $m_i(w)$ at time $t$ is updated as $m_i(w) = t$ if $\|w - q_i\| < r_\mathrm{s}$. Mobile node $i$ can update its information map via direct or indirect communications with node $j$ as $m_i(w) = m_j(w)$ if $m_j(w) > m_i(w)$ and $\|q_j - q_i\| < r_\mathrm{c}$.

To calculate $q_i^\gamma$, a benefit function $\xi_i(m_i, w, t)$ [17] is introduced to evaluate $m_i$ as

$$\xi_i(m_i, w, t) = (t - m_i(w))(\rho + (1-\rho)\varphi_i(w)), \tag{9}$$

where $\rho$ is a weight and $\rho \in (0,1)$. The term $(t - m_i(w))$ is the time span after the cell centered at $w$ has been last visited by node $i$. In (9), $\varphi_i(w)$ [7] is given by

$$\varphi_i(w) = \exp(-\sigma_1\|q_i - w\| - \sigma_2\|q_i^\gamma - w\| - \sigma_3\|h(q_i) - h(w)\|).$$

where $\sigma_1$, $\sigma_2$, and $\sigma_3$ are positive constants. Here, $\sigma_1$ and $\sigma_2$ prioritize positions based on their distances to mobile node $i$ and its current navigation goal, respectively. And $\sigma_3$ is used to prioritize positions based on their elevation differences with node $i$. Mobile nodes should cover positions which have the largest benefit values (i.e. $q_i^\gamma$), which is selected as

$$q_i^\gamma(t+1) = \underset{w \in \tilde{W}_i}{\arg\max}\, \xi_i(m_i, w, t), \tag{10}$$

where $\tilde{W}_i = \{w | w \in W, \|w - q_j\| \ge \|w - q_i\| \ge r_\mathrm{s}, \|q_j - q_i\| < r_\mathrm{c}\}$.

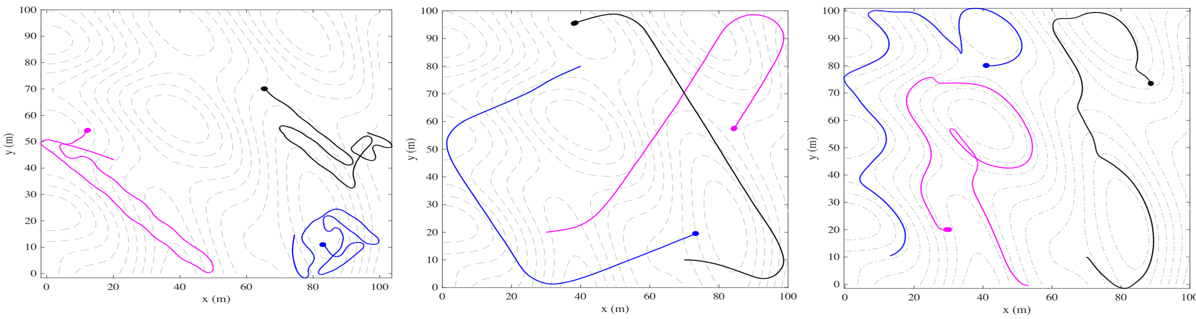
Together with $f_i^c$, the control input of mobile node $i$ moving on a rough terrain is extended as

$$u_i = \begin{cases} f_i^g + f_i^d + f_i^s + f_i^c, & \text{in anti-flocking mode}, \\ f_i^g + f_i^d + f_i^t + f_i^c, & \text{in flocking mode}. \end{cases} \tag{11}$$

For mobile nodes in anti-flocking mode, with the help of the terrain adaptation force and the navigation goal selection method, they can navigate on energy-efficient paths while maintaining a high sensing coverage. The proposed control protocol also helps mobile nodes in flocking mode to find energy-efficient paths for reaching and tracking their targets.

## IV. Performance Evaluation

Tests were conducted to evaluate the performances of the proposed control protocol. The following parameters are fixed for all tests: $c_1 = 2$, $c_2 = 0.6$, $c_3 = 0.5$, $c_4 = 0.1$, $n_\mathrm{min} = 3$, $n_\mathrm{max} = 4$, $r_\mathrm{s} = 10$ m, $r_\mathrm{c} = 18$, $\epsilon = 0.1$, $\rho = 0.2$, $\sigma_1 = 0.04$, $\sigma_2 = 0.01$, and $\sigma_3 = 0.1$. The rest of the parameters are specified separately in each set of simulations. As a quick overview, trajectories of mobile nodes under different control




(a) (b) (c)

Fig. 1: Trajectories of 3 mobile nodes controlled by (a) the semi-flocking control protocol in [12] (b) the anti-flocking control protocol in [17] (c) the proposed energy-efficient semi-flocking control protocol.

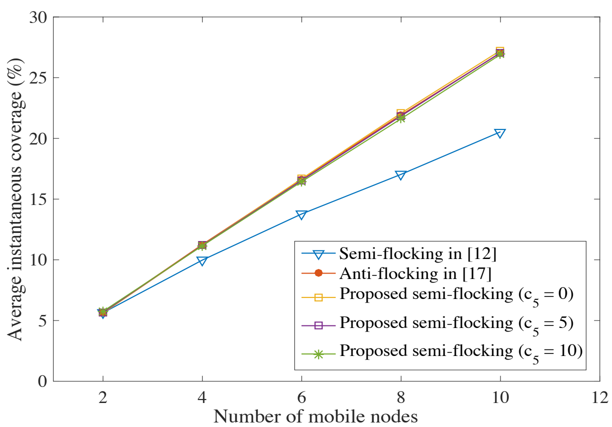



Fig. 2: Average instantaneous area coverage of MSNs with different control protocols under the no-target setup. All data points presented are results of averaging over 100 simulations.

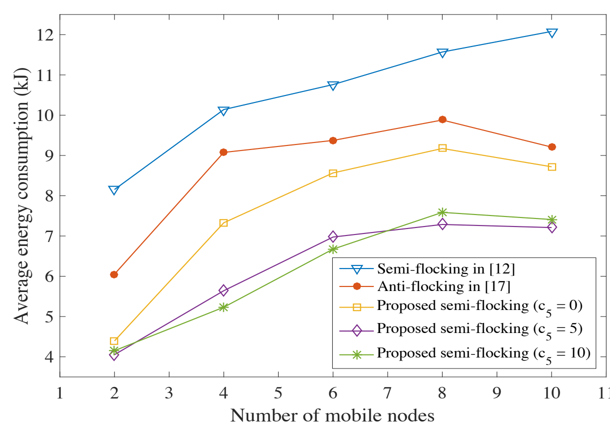



Fig. 3: Average energy consumption (in kilojoules (kJ)) of MSNs during a full scan of the terrain with different control protocols under the no-target setup. All data points presented are results of averaging over 100 simulations.

protocols in one of the experiments are illustrated in Fig. 1. Based on the results, mobile nodes controlled by the semi-flocking in [12] cannot perform effective searching, as each mobile node makes individual navigation decision based on information of its 8 adjacent cells only. Conversely, with the help of information maps, mobile nodes controlled by the anti-flocking control protocol in [17] tend to move along shortest paths between navigation goals on the map and yield a better area coverage. Furthermore, mobile nodes controlled by the proposed control protocol follow contour lines and perform well in area coverage.

### A. *Test Results*

The first set of tests was conducted with no target and the number of mobile nodes was ranging from 2 to 10 for comparing area coverage performances of MSNs with the proposed control protocol and those in [12] and [17]. According to Fig. 2, the proposed semi-flocking control protocols can achieve similar area coverage performances as that in [17], and they both perform much better than that in [12]. Although global navigation information is disseminated to all mobile nodes with the control protocol in [12], the nodes are controlled based on the information of their 8 adjacent areas. Fig. 3 shows the total energy consumption of MSNs during a full scan of the terrain. According to the results, MSNs with the proposed control protocol requires lower energy to complete scans. Furthermore, to evaluate the effect of terrain adaptation force, we compared cases with $c_5 = 0$, $c_5 = 5$, and $c_5 = 10$. It is observed that the proposed control protocol with a mild injection of terrain adaptation force can yield extra energy saving. Details are further discussed in the next section.

The next set of tests was performed with 24 mobile nodes and the number of targets was ranging from 1 to 5 to analyze target tracking performances. Since the anti-flocking control protocol in [17] only focuses on searching the area, the proposed control protocol is only compared with the semi-flocking in [12]. According to the results in Fig. 4, the proposed semi-flocking control protocol can detect all targets faster compared to that in [12]. As illustrated in Fig. 5, the proposed control protocol has used much less energy in finding all the targets. With the help of the terrain adaptation force, the proposed control protocol can further reduce energy consumption by encouraging mobile nodes to find energy-efficient paths for reaching and tracking their targets.

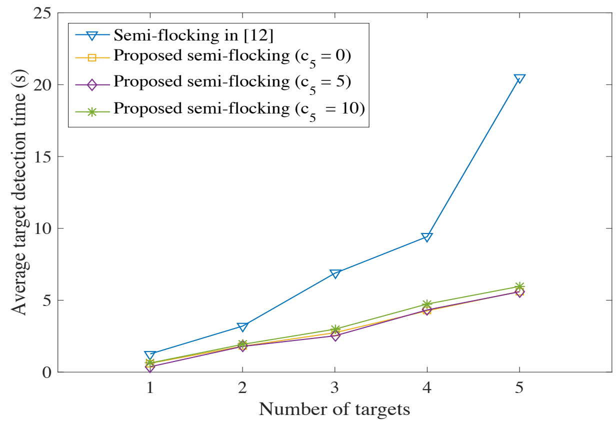



Fig. 4: Average target detection time of MSNs with different control protocols under 24-mobile-nodes setup. All data points presented are results of averaging over 100 simulations.

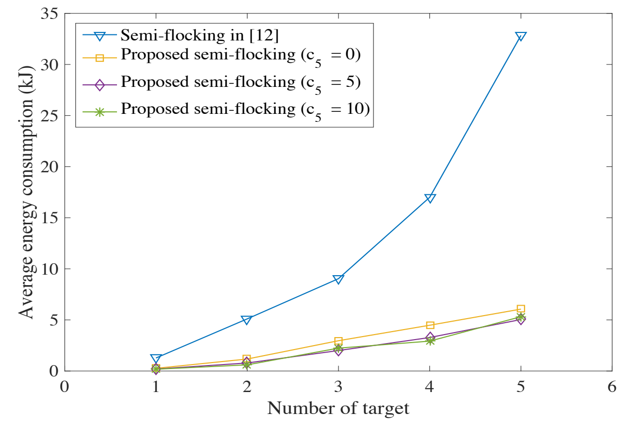



Fig. 5: Average energy consumption (in kilojoules (kJ)) of MSNs for finding all targets on the terrain with different control protocols under 24-mobile-nodes setup. All data points presented are results of averaging over 100 simulations.

## V. Discussion

According to the results, significant reductions in energy expenditure are recorded when changing $c_5$ from 0 to 5, while such improvement diminishes as $c_5$ raises further. The average time of a full scan increases from 309.97 s with $c_5 = 0$ to 348.16 s with $c_5 = 5$, and further to 487.37 s with $c_5 = 10$. Although making nodes to follow contours can reduce changes in elevation and promote energy saving, the proposed control protocol with large $c_5$ takes longer time to finish their scans and result in even higher energy consumption. In (11), the terrain adaptation force imposes a similar influence as the other three forces when $c_5$ is around 2.5 to 5, while it dominates the control when $c_5$ is large. To balance the trade-off between contour following and coverage maximizing, in this paper, $c_5$ is suggested to be set between 2.5 and 5.

## VI. Conclusion

This paper presents an energy-efficient semi-flocking control protocol for monitoring rough terrains with MSNs. A distributed energy-efficient navigation control based on a terrain adaptation force and a navigation goal selection method is introduced to minimize the energy consumption of mobile nodes. Test results demonstrate that MSNs with the proposed semi-flocking control protocol can achieve better area coverage and target tracking performances with lower energy expenditure when compared with some existing control protocols in literature.

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