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A Gravitational Search Algorithm-Based Single-Center of Mass Flocking Control for Tracking Single and Multiple Dynamic Targets for Parabolic Trajectories in Mobile Sensor Networks

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Abstract
Development of an optimal flocking control procedure is an essential problem in mobile sensor networks (MSNs). Furthermore, finding the parameters such that the sensors can reach the target in an appropriate time period is an important issue. This paper offers an optimization approach based upon the metaheuristic methods used for flocking control in MSNs to follow a target. We develop a non-differentiable optimization technique based on the gravitational search algorithm (GSA). Finding the flocking parameters using swarm behaviors is the main contribution of this paper in order to minimize the cost function. The cost function displays the average Euclidean distance of the center of mass (COM) away from the moving target. One of the benefits of using GSA is its application in multiple targets tracking with satisfactory results. The simulation results obtained that this scheme outperforms the existing ones, and demonstrate the ability of this approach in comparison with the previous methods.

Keywords: *Flocking Control, mobile Sensor Network, Target Tracking, Center of Mass, Gravitational Search Algorithms.*

1. Introduction

Wireless sensor networks (WSNs) have been greatly investigated in the past few years [1, 2, 3, 4]. The benefit of mobile sensor networks (MSNs) over the stationary ones is the environmental change adjustment [4]. Hence, MSNs can be used in various domains such as target tracking for protection of the exposed kinds of plants and underwater target observation [6, 7].
Flocks of agents are applicable to many areas including the distributed sensing, formation flying, cooperative surveillance, and point-to-point mail delivery. This phenomenal has been attracted in physics [8], mathematics [9], and biology [10]. Flocking problems have become a major thrust in the system and control theory in the recent years [11].
Cooperative control between mobile sensors is essential due to collision among them [12]. Flocking control [11] is used to resolve this issue. Flocking is a group of several mobile sensors with local interactions with an overall objective [13]. These sensors are capable of splitting, rejoining, and forming highly ordered fast convergence of COM towards the target.
Three rules have been presented by Reynolds [14]. They are considered as what follow.
Flock Centering: Each sensor attempts to remain near its neighbors (cohesion).
Collision Avoidance: The sensors keep away from collision with their neighbors (separation).
Velocity Matching: The sensors try to adjust their speed with their neighbors (alignment).
After the first flocking approach, various algorithms have been proposed for this issue. A survey on the application of flocking control has been investigated in [15]. Olfati-Saber [11] has introduced two algorithms for distributed flocking. The first one is working in free space. The second one is exhibiting this problem regarding the obstacles. In [16], flocking of robots

has been investigated with a virtual leader. Two extended flocking control algorithms, one of which being flocking control with a minority of informed agent [17] and the other one being flocking of sensors with a virtual leader of varying velocity, have been proposed by Su et. al [17]. Multi-target tracking [18] is another benefit of MSN in the dynamic mode. This approach requires that some robots split from the present sensors to follow a new target. If one target disappears in MSN, the robots following that should merge with the present robots that are still following the target. Random selection (RS) and seed growing graph partition (SGGP) are the algorithms that are used for solving the problem of robot splitting/merging in multi-target tracking [19].

Improvement of the performance of target tracking regarding the obstacle using Multi-COM and Single-COM has been presented in the flocking control with single-COM and Multi-COM in [20-22]. Moreover, in order to solve the problem of designing an optimal flocking control in the obstacle space, they used genetic algorithms [23]. Some algorithms have been presented in [24] and [25], which are applicable to homogeneous MSNs. References [26, 27] follow some models for distributed flocking control. However, these works only consider the behavior of the flock without addressing target tracking.

The recent research areas have converged to the arrangement problems in stationary and MSNs [28]. A new category of the emergent motion control algorithms is anti-flocking control algorithms that dynamic coverage performances improve in MSN [29]. The AI optimization methods have been considered in many research domains. The Tabu search algorithm has been employed for optimal design of a MIMO controller [30]. GA, PSO, and ACO have been exploited to design a rotational inverted pendulum system [31]. Stability analysis and configuration control of groups of sensors have been optimized in the recent years [32]. Meanwhile, in [20], the problem of designing a flocking control approach for mobile agents to follow the moving target is advanced. Designing a network to converge to the optimal solution in an appropriate time is an open investigation problem.

Natural-inspired algorithms are robust tools used in solving many optimization problems [33]. Gravitational Search Algorithm (GSA) is a recently introduced nature-inspired method whose idea is the gravity and Newton lows [34, 35]. The results of [33-42] indicate that GSA and its advanced versions are appropriated tools in solving many optimization problems. Therefore, the strength of this algorithm encourages us to apply this method to find the optimal flocking forces.

The main contributions and novelty of this work can be summarized as what follow:

- GSA is adopted to solve the non-differentiable problem in the flocking control design to compute the coefficients of the interaction forces in the cost function to minimize the error between the moving target and the center of flocking.
- Single target moving with a circular wave trajectory is simulated to compare the performance of the proposed method with the previous ones.
- Multiple targets moving with a semi-circular and semi-sine wave trajectory are simulated to evaluate the proposed method.
- The optimal flocking control for single and multiple dynamic target trackings is presented by adding Single-COM to the parabolic trajectories.

This paper is organized as what follow. In Section 2, we introduce the Single-COM flocking control algorithm in the free space for single and multiple dynamic target trackings. In Section 3, we investigate the gravitational search algorithm. In Section 4, the problem of flocking control is formulated and the proposed method is elaborated. In Section 5, we evaluate the performance of the proposed scheme. Finally, in Section 6, we give the conclusions.

2. Flocking control in MSN

2.1. Flocking control approach in free space

A topology of flocks is shown by a graph T that includes a vertex set $v = \{1, 2, ..., m\}$ and an edge set $E \subseteq \{(x, y) : x, y \in v, x \neq y\}$. Each vertex shows one agent of flocks, while the communication link between the two agents is denoted by each edge.

$q_x, p_x \in R^n$ are the location and speed of robot x, respectively. A set of neighborhood of robot x at moment τ is defined as:

$$NB_x = \{ y \in v : \| \leq r, v = \{1, 2, ..., m\}, x \neq y \} \quad (1)$$

where, $\| . \|$ is the Euclidean norm in R^n, and r is the neighborhood radius.

A group of moving agents (or sensors) are described with their motion relation as the following:

$$\begin{cases} \dot{q}_x = p_x \\ \dot{p}_x = u_x, x = 1,2,...,m \end{cases} \quad (2)$$

An $\alpha-$ lattice with the following condition is used to model the geometry of flocks [11]:

$$\| q_x - q_y \| = \gamma \quad (3)$$

In the above relation, γ is the distance between robot x and its flock-mate y. In [11], Olfati-Saber has presented a flocking control algorithm in the free space. This approach includes two control inputs as the following:

$$u_x = f_x^{\alpha} + f_x^{mt} \quad (4)$$

The first component f_i^{α} denotes a gradient-based term and a velocity consensus term as:

$$f_x^{\alpha} = \sum_{y \in NB_x^{\alpha}} \phi_{\alpha}(\| q_y - q_x \|_{\sigma}) n_{xy} + \sum_{y \in NB_x^{\alpha}} a_{xy}(q)(p_y - p_x) \quad (5)$$

In this algorithm, $\phi_{\alpha}(z)$ is the action procedure among the sensors and $\| . \|_{\sigma}$ of a vector is a map $R^n \Rightarrow R_+$ explained as $\| z \|_{\sigma} = \frac{1}{\varepsilon}[\sqrt{1+\varepsilon \| z \|^2} - 1]$ [11]. The vector between q_x and q_y is n_{xy}. $a_{xy}(q)$ is the adjacency matrix. For more details, see [11, 20]. The second component of (4) f_x^{mt} is the distributed navigational feedback owing to the group objective.

$$f_x^{mt} = -(q_x - q_{mt}) - (p_x - p_{mt}) \quad (6)$$

where, mt-agent (q_{mt}, p_{mt}) is the dynamic target specified as follows:

$$\begin{cases} \dot{q}_{mt} = p_{mt} \\ \dot{p}_{mt} = f_{mt}(q_{mt}, p_{mt}) \end{cases} \quad (7)$$

Then the extended control protocol (4) is clearly defined as:

$$u_x = \sum_{y \in NB_x^{\alpha}} \phi_{\alpha}(\| q_y - q_x \|_{\sigma}) n_{xy} + \sum_{y \in NB_x^{\alpha}} a_{xy}(q)(p_y - p_x) - (q_x - q_{mt}) - (p_x - p_{mt}) \quad (8)$$

In this relation, the collision avoidance and the velocity matching are contributed by the first two terms, and the end terms explain the dynamic target tracking [11].

2.2. Single-COM flocking control approach in free space

In this section, the flocking control protocol is described by adding Single-COM to the free space. COM is hard to reach the target in the Single-COM flocking control protocol (8). This makes the problem for robots to follow the target. Thus a recent limitation on the COM should be appended to this algorithm. In [20], extended flocking of robots with Single-COM of location and speed of robots are proposed in the obstacle space. Their protocol without obstacles is presented as the follows:

$$u_x = \sum_{y \in NB_x^{\alpha}} \phi_{\alpha}(\| q_y - q_x \|_{\sigma}) n_{xy} + \sum_{y \in NB_x^{\alpha}} a_{xy}(q)(p_y - p_x) - (\overline{q} - q_{mt}) - (\overline{p} - p_{mt}) - (q_x - q_{mt}) - (p_x - p_{mt}) \quad (9)$$

The pair $(\overline{q}, \overline{p})$ is COM of locations and speeds of mobile agents, respectively, specified in (10).

$$\begin{cases} \overline{q} = \frac{1}{m} \sum_{x=1}^{m} p_x \\ \overline{p} = \frac{1}{m} \sum_{x=1}^{m} p_x \end{cases} \quad (10)$$

In relation (9), each robot should know the location and speed of other robots to compute COM $(\overline{q}, \overline{p})$. The details of the algorithm are described in [20]. Finally, based on the La and Sheng's extended algorithm without obstacle, we propose a Single-COM flocking approach with a moving target in free space as (11).

$$u_x = c_1^{\alpha} \sum_{y \in NB_x^{\alpha}} \phi_{\alpha}(\| q_y - q_x \|_{\sigma}) n_{xy} + c_2^{\alpha} \sum_{y \in NB_x^{\alpha}} a_{xy}(q)(p_y - p_x) - c_1^{SC}(\overline{q} - q_{mt}) - c_2^{SC}(\overline{p} - p_{mt}) - c_1^{mt}(q_x - q_{mt}) - c_2^{mt}(p_x - p_{mt}) \quad (11)$$

Here, $(c_1^{\alpha}, c_2^{\alpha})$, (c_1^{mt}, c_2^{mt}), and (c_1^{sc}, c_2^{sc}) are positive constants.

2.3. Multi-target tracking

In the multi-target tracking, each robot uses the Single-COM flocking control algorithm, which handles with one of the different targets (q_{mt_k}, p_{mt_k}) with $k = 1,2,...,N$ presented as (12).

$$u_x = c_1^{\alpha} \sum_{y \in NB_x^{\alpha}} \phi_{\alpha}(\| q_y - q_x \|_{\sigma}) n_{xy} + c_2^{\alpha} \sum_{y \in NB_x^{\alpha}} a_{xy}(q)(p_y - p_x) - c_1^{SC}(\overline{q} - q_{mt_k}) - c_2^{SC}(\overline{p} - p_{mt_k}) - c_1^{mt}(q_x - q_{mt_k}) - c_2^{mt}(p_x - p_{mt_k}) \quad (12)$$

The random selection (RS) algorithm operates to solve the problem of agent splitting/merging for multi-target tracking in MSN. In this algorithm, if the new target appears in the 50% of agents that are following, the present target will be chosen randomly to follow the recent target [18].

3. A Gravitational Search Algorithm (GSA)

GSA was first introduced in [33] as a novel metaheuristic search algorithm. It is basically influenced by the Newtonian laws and the notion of mass interactions [34]. In this way, the position of each mass is represented as a vector consisting of variables. As it is presented in [33], the gravitational mass of object j at the iteration t, $M_j(t)$ is computed as (13), where $fit_j(t)$ is the cost of agent j, and $worst(t)$ is the worst cost of swarms at time t.

$$M_j(t) = \frac{fit_j(t) - worst(t)}{\sum_{k=1}^{N}(fit_k(t) - worst(t))} \quad (13)$$

The overall force acting on the agent j at dimension m from other agents is computed by (14). Based upon the mobility rules, relation (15) shows the acceleration of the agent j in dimension m at time t. Furthermore, the next velocity of the ith agent is calculated by (16). Then the next location of the jth agent would be computed using (17).

$$F_j^m(t) = \sum_{k \in kbest\_set, k \neq j} rand_k G(t) \frac{M_j(t).M_k(t)}{R_{jk}(t) + \varepsilon}(x_k^m(t) - x_j^m(t)) \quad (14)$$

$$a_j^m(t) = \frac{(F_j^m(t))}{(M_j(t))} = \sum_{k \in kbest\_set, k \neq j} rand_k G(t) \frac{M_k(t)}{R_{jk}(t) + \varepsilon}(x_k^m(t) - x_j^m(t)) \quad (15)$$

$$v_j^m(t+1) = rand_j \times v_j^m(t) + a_j^m(t), \quad (16)$$

$$x_j^m(t+1) = x_j^m(t) + v_j^m(t+1), \quad (17)$$

Where, $kbest\_set$ is the collection of k agents that have the best costs. G is a decreasing function that takes the initial value G_0 and is reduced by time. $rand_k$ is a random number in the interval [0,1], ϵ is a small value, and R_{jk} is the Euclidean distance between agents j and k [34, 35].

4. Proposed method

In this work, it was assumed that in the distance between the current and new positions in which the robot is moving, the computational unit of the robot is in the standby mode. Since in this duration a long distance is traversed, it has a suitable effect on power consumption. Also it is assumed that the agents are GPS-enabled. The initial location of robots is random in the space. Meanwhile, the trajectory of target is predefined.

4.1. Problem of flocking control protocol

The problem of control protocol (11) is sought the optimal results of the interaction parameters $(c_1^{\alpha}, c_2^{\alpha})$, (c_1^{mt}, c_2^{mt}), and (c_1^{sc}, c_2^{sc}) that implement the Reynolds rules for delivering the demanded flock behaviour in which the cost function (18) is minimized. Clearly, the pair $(c_1^{\alpha}, c_2^{\alpha})$ is applied to tune the forces between robot x and its flock mates ($\alpha -$robot); pair (c_1^{mt}, c_2^{mt}) is applied to tune the forces between robot x and the dynamic target; and pair (c_1^{sc}, c_2^{sc}) is employed to tune the forces between the canter of flock and the target. These coefficients should be chosen as well in order to maintain the $\alpha-$ lattice formation, while sensors quickly converge to the target. Accordingly, the cost function is introduced as:

$$F = \frac{\sum_{x=1}^{z} \| \overline{q}_x(\tau) - q_x^{mt}(\tau) \|}{z \| \overline{q}_x(\tau = 0) - q_x^{mt}(\tau = 0) \|} \quad (18)$$

In the above relation, z shows the number of $\Delta\tau s$ and the simulation time is $T = z \times \Delta\tau$.

The cost function (18) presents the following terms:

- The average of Euclidean distance between COM and the dynamic target.
- The Euclidean distance of center of flock away from the moving target at the beginning time.

The cost function (18) is explicitly non-convex. Hence, in order to minimize this function, the evolutionary optimization strategy is stable since this mechanism results in a better performance in convergence percentage. GSA [33] is employed to optimize the problem of flocking control.

The term $\| \overline{q}_x(\tau = 0) - q_x^{mt}(\tau = 0) \|$ in the denominator of (18) shows the maximum distance at the beginning time, the sensors being most distant from the moving target. Moreover, the other term $\| \bar{q}_x(\tau) - q_x^{mt}(\tau) \|$ is the distance of the target away from COM at time τ. During the target tracking, this distance is decreased using the flocking control protocol (11). Decreasing the cost function depends upon how the coefficients of the interaction forces (c_1^α, c_2^α), (c_1^{mt}, c_2^{mt}), (c_1^{sc}, c_2^{sc}) are found out.

4.2. GSA-based Single-COM flocking control

In this section, GSA is adopted to solve the non-differentiable (18) in the flocking control design. The coefficients of the interaction forces in the cost function are computed via GSA. The following is a summary of the process:

Step 1. A population in the size M consisting of M possible solutions is generated randomly. Each agent is an array of the flocking parameters. Therefore, each agent X^I can be represented as:

$$X^I = [c_1^\alpha, c_2^\alpha, c_1^{mt}, c_2^{mt}, c_1^{sc}, c_2^{sc}]^I, I = 1, 2, ..., M$$

Step 2. The costs of agents are calculated by the cost function (18). All the remaining steps of the algorithm (GSA) would be conducted as described in Section 3. The best solution found by the algorithm is considered as the optimal array of the interaction parameters.

Algorithm 1 briefly shows the procedure of the proposed method.

Algorithm 1. Procedure of the proposed method

1.	Identify search space
2.	Generate random solutions considering X^I
3.	Evaluate fitness function:
3.1.	Update position of sensor x
3.2.	Update velocity of sensor x
3.3.	Compute distance between COM and a moving target.
3.4.	Compute fitness value by (18)
4.	Update $M_j(t)$ using (13)
5.	Calculate total force in different directions using (14).
6.	Calculate acceleration and velocity using (15) and (16).
7.	Update positions using (17)
8.	Repeat steps 3-7 until stopping criterion is satisfied.

5. Results and Discussion

In order to evaluate the performance of the proposed method, some experiments were conducted. We simulated a single target moving with circular wave, and the multiple targets moving with a semi-circular and semi-sine wave trajectory. The parameters were set as follow:

- GSA parameters : The search space of the coefficients of the interaction forces is considered between 0 and 10 $1 \le (c_1^v, c_2^v) \le 10$ for $v = \alpha, mt, sc$). Both the number of iterations and the population size were set to 100. G is a linearly decreasing function starting with $G_0 = 0.125$ and ending with 0. The optimal value for G_0 is computed by the trial-and-error method.
- Parameters of flocking control in the free space: the number of sensors is 50, and the initial position of sensors is randomly distributed in the space $[0, 90] \times [0, 90]$. The parameters a and b are equal to 5 (for $\phi(z)$ [12]). For σ-norm, $\varepsilon = 0.1$; $h = 0.2$ for $\phi_\alpha(z)$. The coordinate radius is $r = 1.2\gamma = 7.5$.
- Parameters of single dynamic target: path of moving target is the circular wave path: $q_{mt} = [210 - 100\cos(\tau), 105 + 80\sin(\tau)]^T$, where τ is $0 \le \tau \le 5.5$ and $p_{mt} = (q_{mt}(\tau) - q_{mt}(\tau - 1)) / \Delta\tau$.
- Parameters of multiple moving targets: path of thev moving target is the semi-circular wave path: $q_{mt} = [130 - 90\cos(\tau), 250 + 30\tau + 80\sin(\tau)]^T$, where τ is $0 \le \tau \le 6$, and $p_{mt} = (q_{mt}(\tau) - q_{mt}(\tau - 1)) / \Delta\tau$.
  Path of the moving target is the semi-sine wave path: $q_{mt} = [200 + 40\tau, 50 + 50\tau + 150\sin(\tau)]^T$ where τ is $0 \le \tau \le 6$, and $p_{mt} = (q_{mt}(\tau) - q_{mt}(\tau - 1)) / \Delta\tau$.

$\Delta\tau$ is equal to 0.05 in this simulation experiment (see Figure 1).

Comparative methods: In order to indicate the superiority of the proposed method, this protocol was compared with two methods that have been proposed in the literature works. The former method is the flocking control in the free space that has been proposed by Reza Olfati-Saber [11] and the later one is the extended flocking control with Single-COM that has been proposed by Sheng and La in [19]. These methods use relations (4) and (9), respectively. The experiments are performed on single and multiple moving target trackings.

The optimal values for the interaction forces including (c_1^α, c_2^α), (c_1^{mt}, c_2^{mt}), and (c_1^{sc}, c_2^{sc}) are found using GSA regarding (11) for various sizes of robots. The results obtained are reported in table 1 by varying the number of sensors as 10, 30, 50, 70, and 90. Figure 1 shows the results of single target tracking on circular wave trajectory for the proposed method, which obtains the optimal parameters using GSA (as in Table 1); also figures 2 and 3, respectively, show the results of the flocking control algorithm without COM [11] and the extended flocking control algorithm with Single-COM [20]. Figure 4 represents the result of the multiple moving target trackings on the semi-circular and semi-sine wave trajectories using the parameters achieved by GSA for single target tracking. The results reported in table 1 are also applicable to the multiple mode. It is clearly observable that the center of flocks precisely tracks the moving targets. Figures 5 and 6, respectively, illustrate the results of the flocking control algorithm without COM [11] and the extended flocking control algorithm with Single-COM [20] in multiple moving target trackings.

In these figures, the path of target and the mean of positions of all robots are displayed in red and black, respectively. Also the initial and end positions of all robots are indicated. As it can be observed in figures 1 and 4, the targets are followed precisely and surrounded by the flocks of robots. In fact, the path of COMs coincides with the path of targets in the proposed method, while according to figures 2 and 5 that use the method proposed by Olfati-Saber [11] and figures 3 and 6 that use the Single-COM method presented by Hung La [20], the paths do not coincide and the distance between the targets and the center of flocks is high.

Figure 7(a) shows the mean progress of the cost function (18) for 50 sensors during 100 iterations by GSA. The results obtained are averaged over 10 independent runs, as the results reported in table 1. Figure 7(b) shows the distance between the center of flock and the moving target in circular wave trajectory using GSA during 100 iterations of the algorithm.

Figures 8(a) and 8(b) compare the errors between COM (center of mass) of the locations of robots and the location of a moving target (following performance) using three approaches, No-COM [11], Single-COM without iteration forces [20], and the proposed flocking protocol using the optimal parameters of table 1 for 50 sensors. Figures 8(a) and 8(b) evaluate three methods on a single moving target and multiple dynamic targets, respectively. These figures obviously display the superiority of the proposed method in comparison with the previous ones, and clearly represent big errors between COM of locations of all agents and the location of the dynamic target for flocking control algorithm without optimal parameters shown in [11] and [20].

Figure 9(a) displays the fitness values during 100 iterations for various numbers of sensors using GSA; and figure 9(b) shows the error between COM and single moving target during target tracking using the data reported in table 1 for various numbers of sensors.

Considering the results reported in figures 1 and 4 by using the optimal flocking control leads to a better convergent speed, and errors reach zero after a few seconds. Also the parameters obtained for single target tracking as figures 4 and 7(b) have optimal results for multiple target trackings.

6. Conclusion

In this work, we investigated the optimization problem of Single-COM flocking control protocol to track a dynamic target for a mobile sensor network. The cost function was non-convex and the optimization technique based on GSA was developed. The optimal interaction forces for different numbers of sensors in the Single-COM flocking control protocol with single and multi-target tracking were proposed. Evaluation of the swarm robots-like act based dynamic target following the free space is given. The numerical results obtained validate the proposed method performance in comparison with the other approaches.

In the future, we have decided to work on the flock behavior in free and obstacle spaces. Also we would like to improve GSA with memetic as well as discussing the flocking control in 3D. In addition, the power consumption analysis is deferred to the future work.

Table 1. Optimal forces of Single-COM flocking control for different sizes found by GSA for various numbers of sensors.

Number of sensors	c_1^{α}	c_2^{α}	c_1^{mt}	c_2^{mt}	c_1^{sc}	c_2^{sc}
10	5.48098	3.73038	4.61782	4.38692	8.45326	3.0838
30	8.24948	3.7478	3.77368	5.0691	5.44878	2.11092
50	8.90246	2.63806	7.05536	4.97568	5.46172	3.4584
70	6.95232	2.17282	3.92754	8.16904	7.35568	3.13232
90	7.71056	3.28264	3.7309	5.27358	6.52208	2.34054

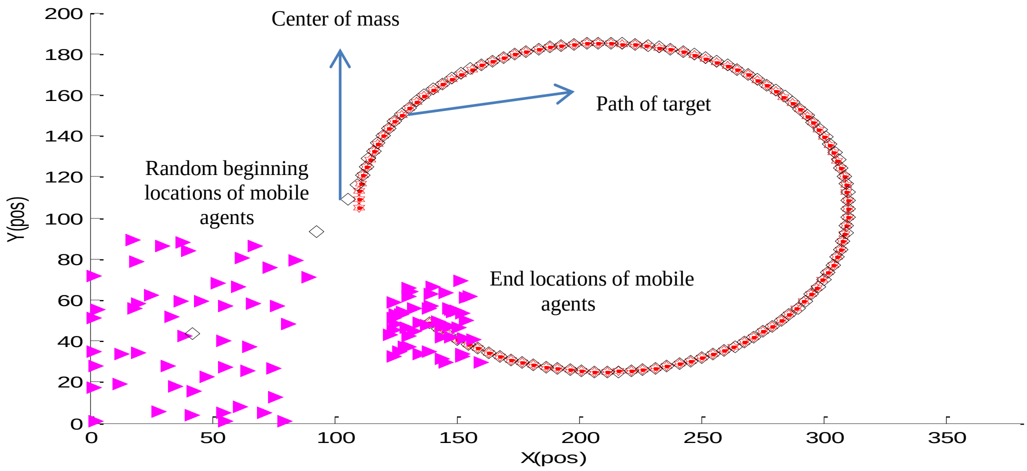

Figure 1. Beginning and ending locations of 50 mobile agents that are following a dynamic target in circular wave path with optimal parameters in table 1 by proposed flocking control algorithm using (11) and GSA.

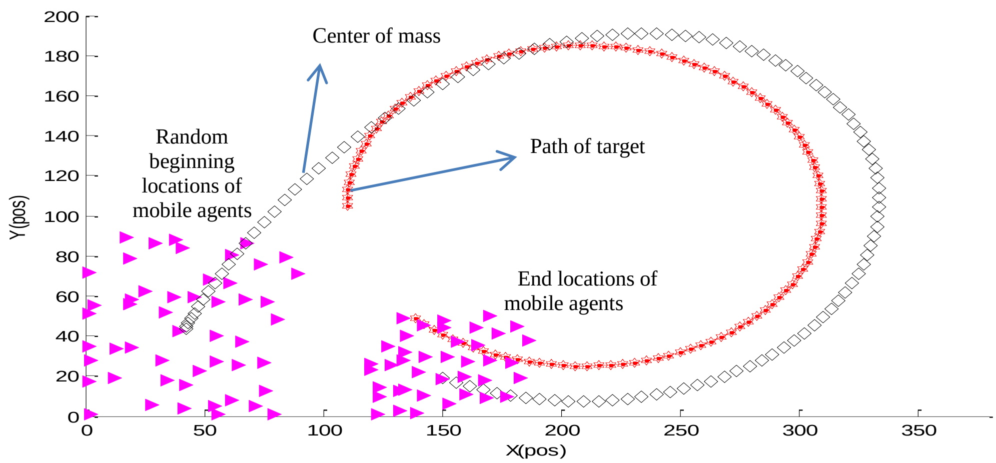

Figure 2. Beginning and ending locations of 50 mobile agents that are following a moving target in circle wave path without iteration forces using (4) [11].

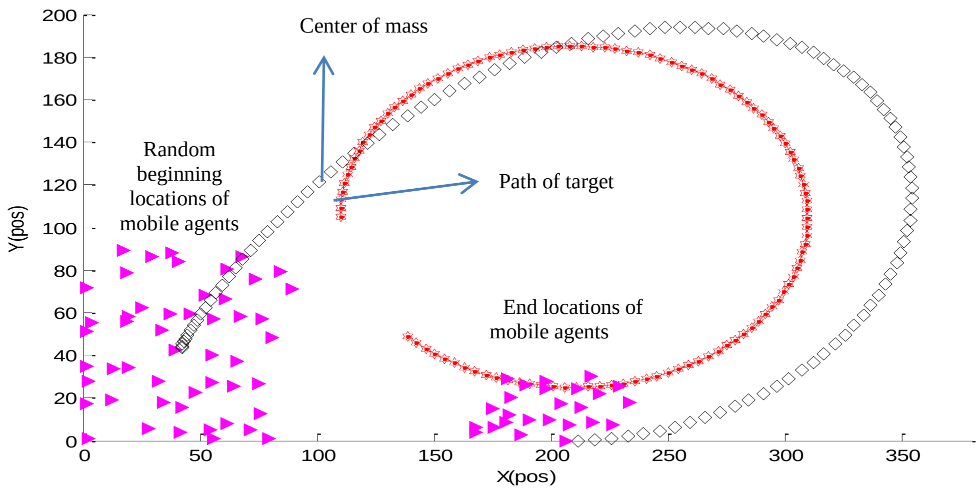

Figure 3. Beginning and ending locations of 50 mobile agents that are following a moving target in circle wave path with extended flocking control algorithm using (9) [20].

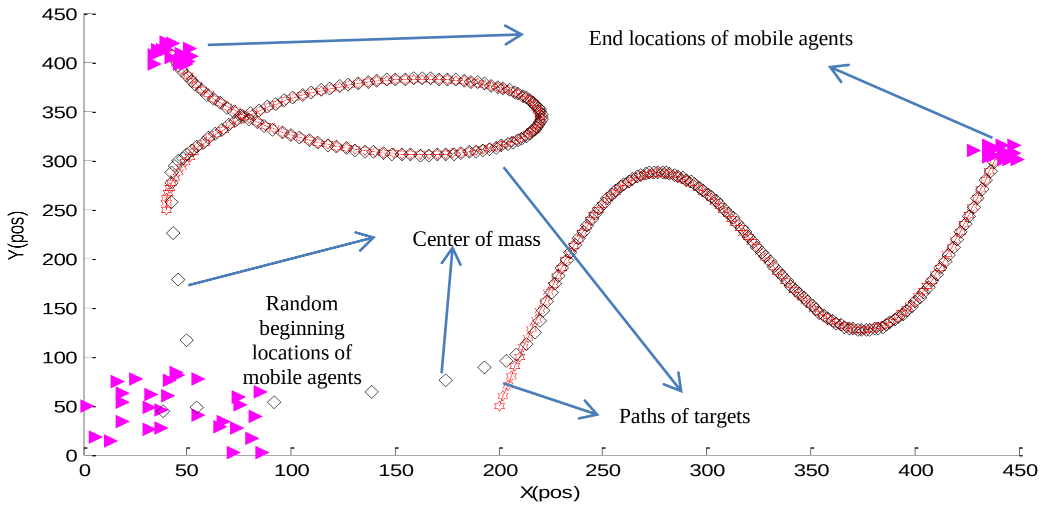

Figure 4. Beginning and ending locations of 30 mobile agents that are following two dynamic targets in semi-circular and semi-sine wave paths with optimal parameters in table 1 by proposed flocking control algorithm using (11) and GSA.

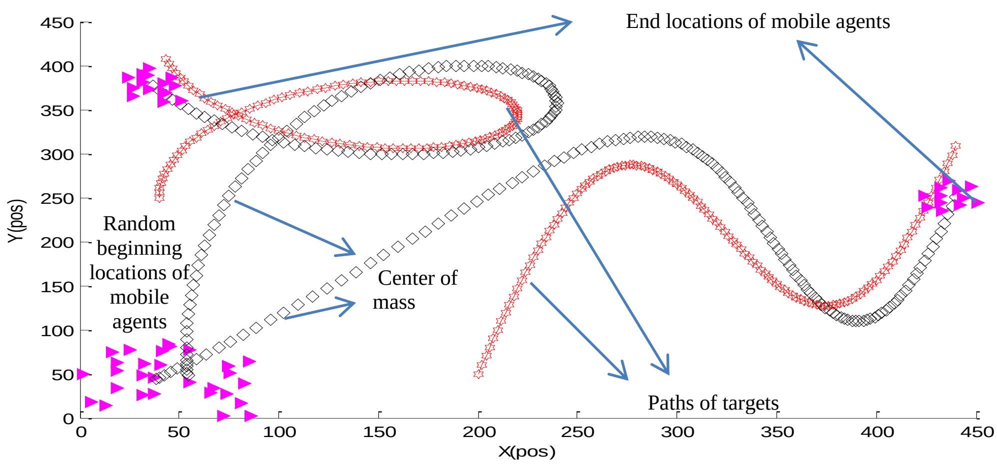

Figure 5. Beginning and ending locations of 30 mobile agents that are following two moving targets in semi-circular and semi-sine wave paths without iteration forces using (4) [11].

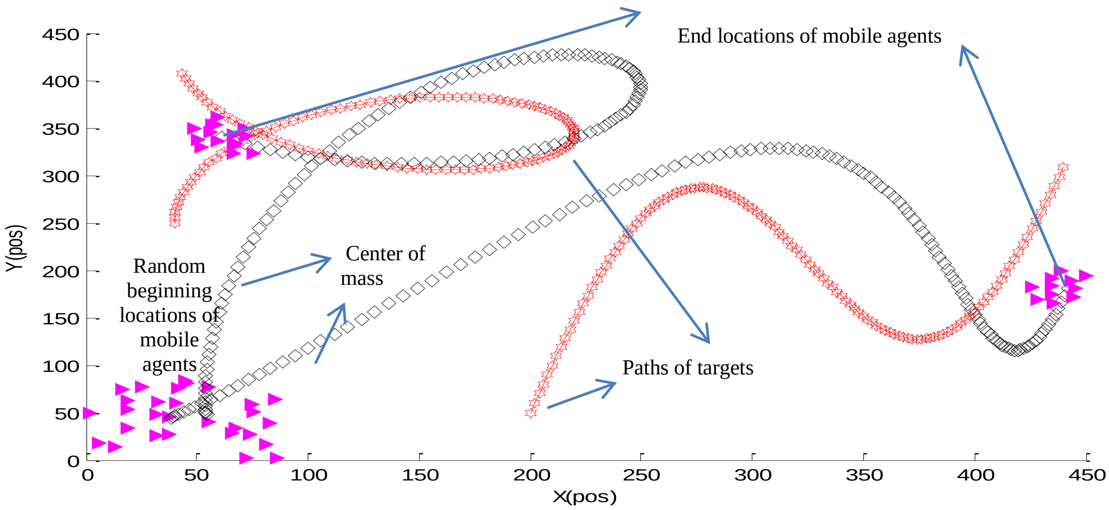

Figure 6. Beginning and ending locations of 50 mobile agents that are following two moving target in semi-circular and semi-sine wave paths with extended flocking control algorithm using (9) [20].

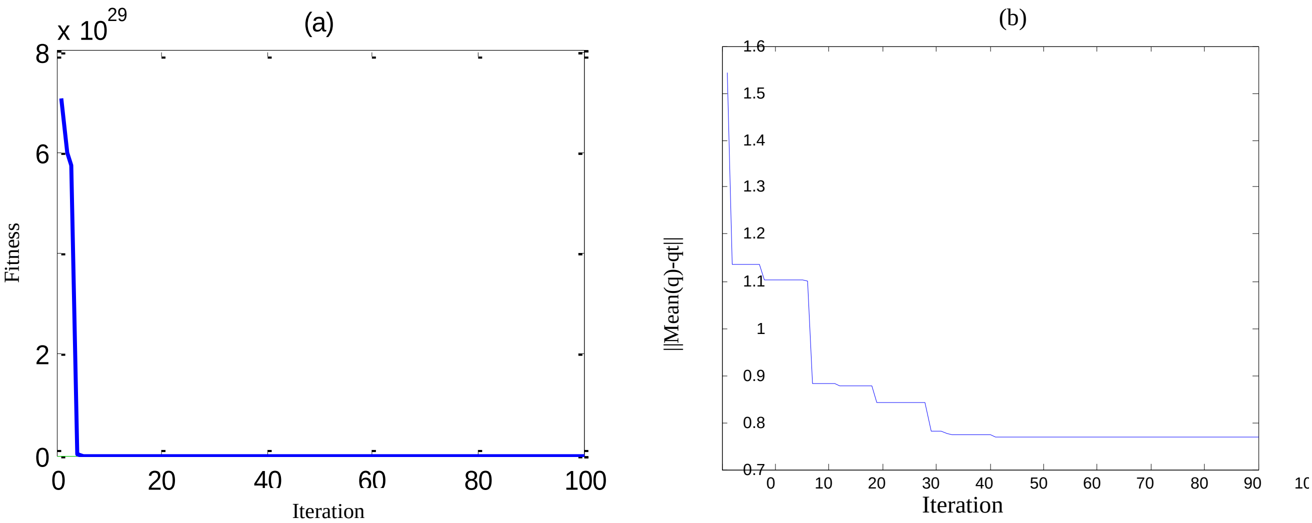

Figure 7. (a) Value of cost function during 100 iteration for 50 sensors, (b) errors between COM of locations of robots and location of target during 100 iterationa for 50 sensors.

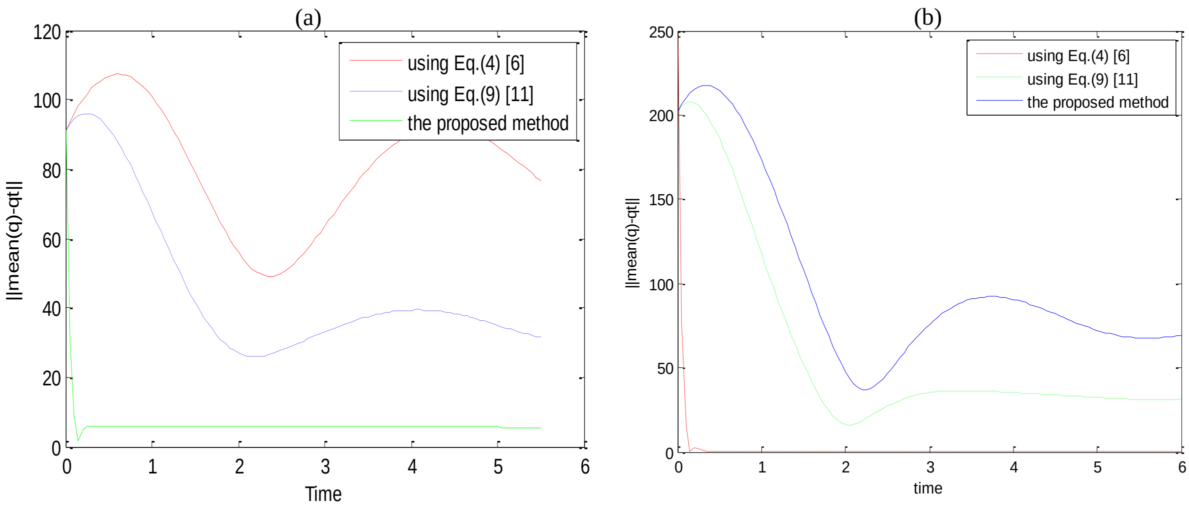

Figure 8. (a) Errors between COM of locations of robots and location of target in circular trajectory, (b) errors between COM of locations of robots and locations of two targets in semi-circular and semi-sine trajectory; all following processes for three algorithms are done on 50 sensors.

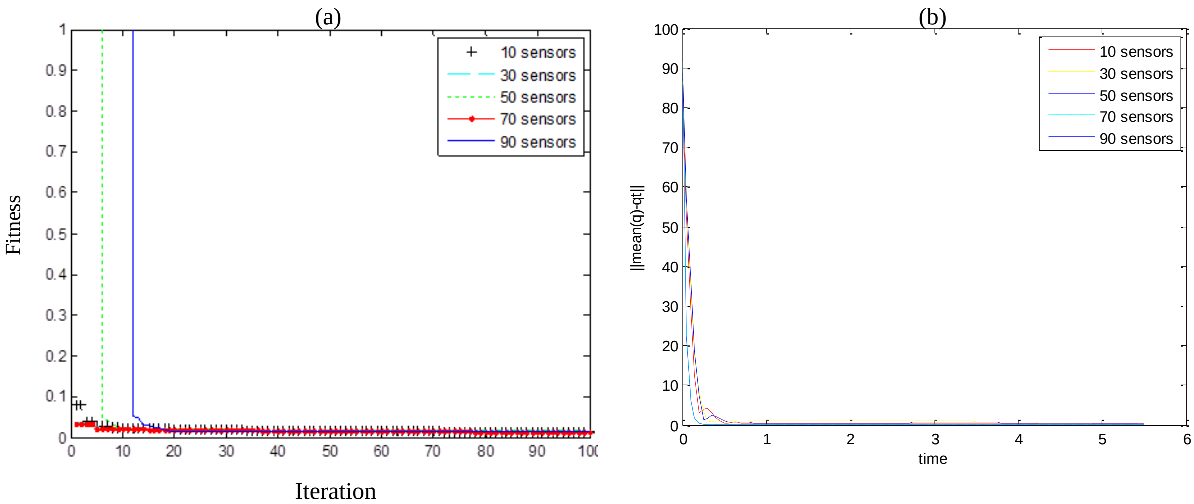

Figure 9. (a) Value of cost function for various numbers of sensors during 100 iterations, (b) errors between COM of locations of robots and location of target in circular trajectory for different numbers of sensors.

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نشریه هوش مصنوعی و داده کاوی

یک الگوریتم جستجوی گرانشی براساس کنترل توده با مرکز توده-منفرد برای ردیابی یک یا چند هدف پویا در مسیرهای سهمی برای شبکه های حسگر متحرک

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چکیده:

پیشرفت رویه کنترل توده بهینه، یکی از مشکلات اصلی در شبکه های حسگر متحرک می باشد. علاوه بر این، یکی از مسائل مهم در این شبکه ها پیدا کردن پارامترهای بهینه است بنحوی که حسگرهای متحرک با بهترین سرعت به سمت هدف پویا همگرا شوند و به خوبی زمان ردیابی را کاهش دهند. این مقاله یک الگوریتم کنترل توده بهینه برای ردیابی هدف پویا در شبکه های حسگر متحرک براساس متدهای فراابتکاری ارائه می‌کند. ما در این مقاله از یک روش بهینه‌سازی غیر محدب براساس الگوریتم جستجوی گرانشی بهره برده‌ایم. هدف کلی این مقاله پیدا کردن پارامترهای بهینه برای الگوریتم کنترل توده است تا رفتارهای گروهی خواسته شده را برای کم کردن تابع برازندگی انجام دهد. تابع برازندگی میانگین فاصله اقلیدسی مرکز توده از هدف پویا می باشد. یکی از مزیت‌های استفاده از الگوریتم جستجوی گرانشی، کاربرد آن در ردیابی چند هدف با نتایج رضایت بخش است. نتایج شبیه‌سازی، کارایی الگوریتم جستجوی گرانشی را در مقایسه با کارهای گذشته به وضوح نشان می‌دهد.

کلمات کلیدی: کنترل توده، ردیابی هدف، شبکه حسگر متحرک، مرکز توده، الگوریتم جستجوی گرانشی.