Herding Predators Using Swarm Intelligence

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***Abstract*—Swarm intelligence, a nature-inspired concept that includes multiplicity, stochasticity, randomness, and messiness is emergent in most real-life problem-solving. The concept of swarming can be integrated with herding predators in an ecological system. This paper presents the development of stabilizing velocity-based controllers for a Lagrangian swarm of $n \in \mathbb{N}$ individuals, which are supposed to capture a moving target (intruder). The controllers are developed from a Lyapunov function, total potentials, designed via Lyapunov-based control scheme (LbCS) falling under the classical approach of artificial potential fields method. The interplay of the three central pillars of LbCS, which are safety, shortness, and smoothest course for motion planning, results in cost and time effectiveness and efficiency of velocity controllers. Computer simulations illustrate the effectiveness of control laws.**

***Index Terms*—swarm, artificial potential field, Lyapunov stability, velocity controllers**

I. INTRODUCTION

A swarm is a well-organized and coherent mechanism that depicts a group or collection of organisms [1]. Swarm-based algorithms are a form of population-based algorithm inspired by nature that can produce low-cost, efficient, and reliable solutions to a variety of challenges. For instance, the possible use of groups of robots (cellular robots) that could work like cells of an organism to assemble more complex parts [2], or the use of swarm of unmanned aerial vehicles (UAVs) in monitoring air pollution caused by gases released by industries [3]. Swarm Intelligence (SI) is a relatively recent development of artificial intelligence (AI) which is used to model the collective behavior of social swarms throughout nature including ants, honey bees, and bird flocks [4]. Computational models inspired by natural swarm systems are linked to this as swarm intelligence models. Several swarm intelligence models based on multiple natural swarm methods have been designed in literature [1], [5]–[13]. The concept of a swarm suggests multiplicity, stochasticity, randomness, and messiness, and the concept of intelligence suggests that the problem-solving method is successful [14].

According to Volmerg (1979), he argued that the repetitive character of the modern job gives rise to the mental state of monotony [15]. Hence swarm intelligence is used in such cases to reduce human interaction for trivial jobs. Jobs that are risky or dirty are also of concern when human interaction is discussed. In many such cases, robots are utilized to carry out the course. This not only reduces human efforts but also prevents one from risks of injuries and dangerous diseases [16], [17]. Swarm is also utilized in the areas of transportation. Transporting parcels in some areas could be challenging, hence robots are nowadays heavily used to do this job. Even in health care units, swarm intelligence is utilized. In Pandemic like COVID-19, swarms of robots can be used for delivering medicines.

Over the past years, the field of swarm robots has been greatly utilized and has shown great results in any associated area it has been used [18]. In a study conducted in the year 2001, the researchers stated some admirable advantages of swarming in businesses. These involve flexibility, robustness, and self-organization. Flexibility in a sense, employees can adapt to sudden changes that may arise in the workplace. Robustness is when one or two members of the group fail to perform their task but the entire group can still function. Lastly, self -organization includes minimum supervision also known as top-down control. The members can function with minimum instructions [19].

This paper aims to highlight biological swarming, where it draws attention towards herding predators using swarm intelligence. According to researchers, biological swarming is divided into two major approaches namely, Eulerian and the Lagrangian approaches [20]. In the context of predator and prey, the swarm could be of great importance. For instance, protecting livestocks. In many cases, it is very difficult to monitor livestock and keep them protected. In addition, it is very dangerous at times for humans to protect livestock from predators such as lions and other life-threatening and wild animals. Thus, this paper shall outline one alternative means as to how predators can be kept away from our livestock or even our domesticated animals. The paper shall also fill in the missing links from the previous studies. It shall provide a more sustainable approach using the artificial potential field concept where predators can be monitored by prey and humans with safety measures. The above will be achieved by constructing stabilizing velocity controllers of each individual of a swarm of $n \in \mathbb{N}$ individuals and a intruder. The velocity controllers will be derived from a total potential called a Lyapunov function, which is developed using the Lyapunov-based control scheme (LbCS).

The remainder of the paper is organized as follows: Section

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II discusses some of the related works. In Section III, the LbCS is discussed briefly. Section IV provides the system modelling for a two dimensional swarm model with a moving target (intruder). The velocity control laws are derived for the swarm individuals and the moving target from a Lyapunov function in Section V. Section VI provides the stability analysis of the proposed system. Simulation results are presented in Section VII. Finally, the paper is concluded in Section VIII.

II. RELATED WORK

The idea of swarming is originally from the field of Biology. A study conducted on algorithms for swarming based on competitive predators with dynamic virtual teams stated, competition results in predation and thus, there was a need for addressing this problem. A Fitness Predator Optimizer (FPO) was designed which monitored the predator's search behavior, at the same time having self-awareness [21]. Another study named An Empirical Comparison of Particle Swarm and Predator-Prey Optimisation (PSO) also agrees with this. PSO study shows the balancing of exploration and exploitation. A similar concept was used in this study as the FPO. The study defined two populations of particles. First, as the population particles of predators. The second is the swarm particle of prey. They observed that predators had different dynamic behavior towards the prey. These predators are attracted to the best individuals in the swarm and others repelled [22]. A similar study named, Predator-Prey Brain Storm Optimization for DC Brushless Motor BSO also shows similar findings as to PSO. Here clusters were defined and the centers act like the predators, which moved towards favorable positions. On the other hand, the prey moved away or rather repelled from the predators [23].

Literature states that researchers have been trying to understand and model swarming behavior [24]–[26]. There are two types of approaches: nonspatial and spatial [24]. The non-spatial approach is characterized as the swarming dynamics at the population level in terms of frequency distributions of groups of various sizes in nonspatial techniques [24]. Based on innate group dynamics, environmental factors, and interactions with other groups, it is thought that groups of varying sizes divide or merge into other groups [24]. However, literature has noted that the disadvantage of nonspatial techniques is that to describe and evaluate population dynamics, they require multiple artificial assumptions regarding fusion and fission of groups of various sizes [24].

The spatial approach includes space (environment) in the model and analysis, either explicitly or implicitly. This approach can be divided into two distinct frameworks; Lagrangian framework (individual-based) and Eulerian framework (continuum) [1], [6], [7], [9], [11], [24], [27]. In the Lagrangian framework, the state of an individual and its relationship with other individuals in the swarm are investigated [1], [6]. Within this framework, it is widely accepted that swarming behavior is caused by a combination of long-range attraction and short-range repulsion between individuals [24]. In the Eulerian framework, the swarm is regarded as a continuum, defined by its density in one, two, or three dimensions. Partial differential equations describe the evolution of swarm density over time [1], [6], [7], [9], [11], [24], [27]. The advection-diffusion-reaction equation is the fundamental equation of Eulerian models, in which advection and diffusion are the combined outcomes of individual behavior and environmental factors, while the response term is related to population dynamics [24].

III. LYAPUNOV-BASED CONTROL SCHEME

The Lyapunov-based Control Scheme (LbCS) is commonly used in robotics research for motion planning and control of numerous robotic systems [**?**], [12], [17], [28]–[31]. The LbCS falls under the artificial potential field method of the classical approach, and has been effectively used to construct continuous time-invariant nonlinear velocity or acceleration controllers as shown in [32]–[37], and [38].

An effective and controlled motion of a robot can be achieved using the method of LbCS by appropriately designing attractive and obstacle avoidance functions. LbCS adopts a strategy of developing a repulsive potential field function that fundamentally is a ratio that encodes the obstacle avoidance function into its denominator while the numerator consists of a tuning parameter [6], [11], [27]. This ratio is known as the repulsive potential field function and ensures the avoidance of obstacles. An attractive field is applied to the target and a repulsive field to each obstacle. Furthermore, the workspace is saturated with positive and negative fields, whereby the technique of steepest descent and total potential gradient helps guide the movement, speed, direction and orientation of the robot.

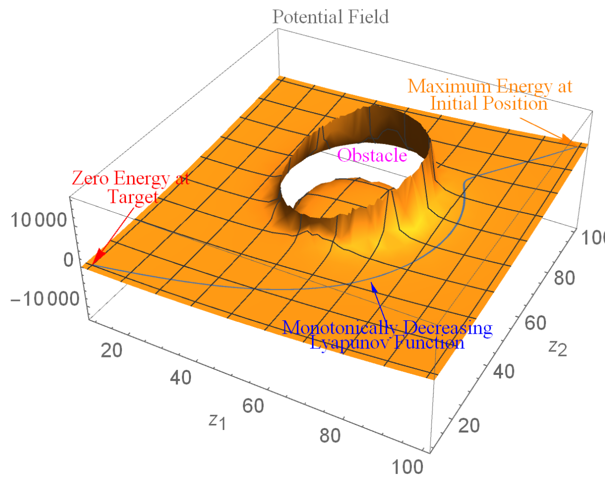
A demonstration of a Lyapunov function is given below in Fig. 1 where the contour plot and 3D visualisation in a workspace for a robot whose initial position is at (100,100) is presented. The robot's trajectory from its initial location to its target position (10, 10) is depicted by the dotted line, which shows the robot avoiding the obstacle at (65, 60) with radius 20.

IV. SYSTEM MODELLING

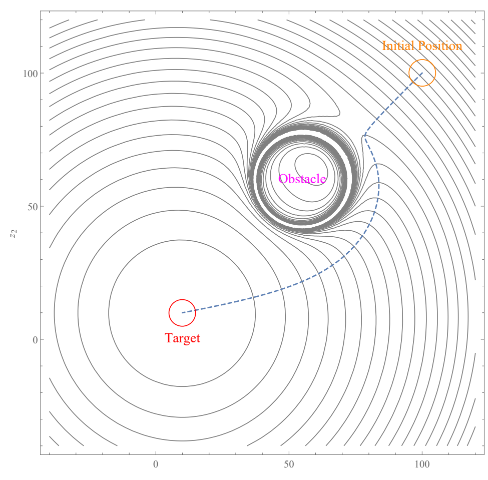
Lets consider a real-life situation where $n \in \mathbb{N}$ policemen or security guards who are scattered in an environment to prevent an intruder to reach its desired location. The objective of this section is to develop a swarm-intruder system, to stop/capture a intruder, once detected, to reach its target location using $n \in \mathbb{N}$ swarm individuals. The swarm individuals could communicate with each other, that is, they are connected in a network.

A. A two-dimensional swarm herding predator model

Consider a swarm of $n \in \mathbb{N}$ individuals and a intruder that are treated as rigid bodies. The $n \in \mathbb{N}$ individuals will be used to build a generic swarm model. The independent parameters, particularly are the translational components, which will be used to define the locations of the swarm individuals and the intruder in a 2-D configuration.



(a) 3D visualisation of a Lyapunov function.



(b) Contour plot for the Lyapunov function.

Fig. 1. An illustration of Lyapunov-based Control Scheme.

Definition 4.1: The i^{th} individual of the swarm positioned at (x_i, y_i) and radius $r_i > 0$. It could be described as the set

$$H_i := \{(z_1, z_2) \in \mathbb{R}^2 : (z_1 - x_i)^2 + (z_2 - y_i)^2 \le r_i^2\}. \quad (1)$$

Definition 4.2: The centroid of the swarm *of* $n \in \mathbb{N}$ *individuals is*

$$\boldsymbol{x}_C = (x_C, y_C) := \left(\frac{1}{n} \sum_{k=1}^{n} x_k, \frac{1}{n} \sum_{k=1}^{n} y_k \right). \quad (2)$$

Definition 4.3: The intruder is a disk with center $\boldsymbol{x} = (x, y)$ *and radius* $r_a > 0$. *It is described by the set*

$$\tau_1 := \{(z_1, z_2) \in \mathbb{R}^2 : (z_1 - x)^2 + (z_2 - y)^2 \le r_a^2\}. \quad (3)$$

Let the positions of the i^{th} individual of the swarm and the intruder at time $t \ge 0$ be $\boldsymbol{x}_i = (x_i(t), y_i(t))$, for all $i \in \{1, 2, 3, \dots, n\}$ and $\boldsymbol{x} = (x(t), y(t))$, respectively, with $(x_i(t_0), y_i(t_0)) = (x_{i_0}, y_{i_0})$ and $(x(t_0), y(t_0)) = (x_0, y_0)$ as the initial conditions. By suppressing t, let $\boldsymbol{x}_i := (x_i, y_i) \in \mathbb{R}^2$ and the state vectors be $\mathbf{x} := (\boldsymbol{x}, \boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \dots, \boldsymbol{x}_n) \in \mathbb{R}^{2n+2}$. Also, let $\mathbf{x}_0 = (x_0, y_0, x_{1_0}, y_{1_0}, x_{2_0}, y_{2_0}, \dots, x_{n_0}, y_{n_0}) \in \mathbb{R}^{2n+2}$.

The instantaneous velocity of the i^{th} swarm individual and the intruder at $t \ge 0$ are $(v_i(t), w_i(t)) := (x_i'(t), y_i'(t))$ and $(\sigma(t), \delta(t)) := (x'(t), y'(t))$, respectively. From the above notations, a system of first-order ODEs for the i^{th} swarm individual and the intruder are formed as:

$$x_i'(t) = v_i(t), y_i'(t) = w_i(t),$$

and

$$x'(t) = \sigma(t), y'(t) = \delta(t),$$

respectively. If the instantaneous velocity for the i^{th} swarm individual (v_i, w_i) and the intruder (σ, δ) have a state feedback law of the form,

$$v_i(t) = -\mu_i f_i(\mathbf{x}(t)), \ w_i(t) = -\varphi_i g_i(\mathbf{x}(t)),$$

and

$$\sigma(t) = -\Omega p(\mathbf{x}(t)), \ \delta(t) = -\mho q(\mathbf{x}(t))$$

for scalars $\mu_i, \varphi_i, \Omega, \mho > 0$ and functions $f_i(\mathbf{x}(t))$, $g_i(\mathbf{x}(t))$, $p(\mathbf{x}(t))$, and $q(\mathbf{x}(t))$ to be constructed accordingly later. Let $\mathbf{g}_i(\mathbf{x}) := (-\mu_i f_i(\mathbf{x}), -\varphi_i g_i(\mathbf{x})) \in \mathbb{R}^2$ and $\mathbf{g}(\mathbf{x}) := (-\Omega p(\mathbf{x}), -\mho q(\mathbf{x})) \in \mathbb{R}^2$ contain the state feedback law of the i^{th} swarm individual and the intruder, respectively. If $\mathbf{G}(\mathbf{x}) := (\mathbf{g}(\mathbf{x}), \mathbf{g}_1(\mathbf{x}), \mathbf{g}_2(\mathbf{x}) \dots, \mathbf{g}_n(\mathbf{x})) \in \mathbb{R}^{2n+2}$, then the swarm of $n \in \mathbb{N}$ individuals and the intruder system is

$$\dot{\mathbf{x}} = \mathbf{G}(\mathbf{x}), \ \ \mathbf{x}(t_0) = \mathbf{x}_0. \quad (4)$$

V. Lyapunov-based Velocity Controllers

Consider the 2-D configuration space of system (4) that has $n \in \mathbb{N}$ swarm individuals and a intruder.

Definition 5.1: The target for the intruder is $\boldsymbol{x}_\tau$. *It is a disk with center* $\boldsymbol{x}_\tau = (a, b)$ *and radius* r_τ. *It is described as the set*

$$\tau_2 := \{(z_1, z_2) \in \mathbb{R}^2 : (z_1 - a)^2 + (z_2 - b)^2 \le r_\tau^2\}. \quad (5)$$

A. Lyapunov function components

Assume that each individual in the swarm is identical; hence $r_i = r_b \ \forall \ i \in \{1, 2, 3, \dots, n\}$ where r_b is the radius of the disk in which the individual is residing.

1) Attraction of swarm individuals towards the swarm centroid: The attractive potential function that will ensure that the ith individual is attracted to the swarm centroid is proposed to be:

$$R_i(\boldsymbol{x}_i) := \frac{1}{2} \left\| \boldsymbol{x}_i - \boldsymbol{x}_C \right\|^2 \quad (6)$$

for $i \in \{1, 2, 3, \dots, n\}$. This attraction function is to ensure the attraction of the ith individual to the centroid of the swarm.

2) Target attraction of the swarm centroid: The target of the swarm $n \in \mathbb{N}$ individuals is a moving target, which essentially is the intruder, and the following target attraction function ensures that the centroid of the swarm is attracted to the intruder:

$$T(\mathbf{x}) := \frac{1}{2} \left\| \boldsymbol{x}_C - \boldsymbol{x} \right\|^2. \quad (7)$$

3) Inter-agent collision avoidance: This repulsion function ensures there is an inter-agent collision avoidance between the ith and jth individual where $j \neq i$ and $i, j \in \{1, 2, 3, \ldots, n\}$. We consider the function

$$Q_{ij}(\boldsymbol{x}_i) := \frac{1}{2}\left[\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2 - (2r_b)^2\right]. \tag{8}$$

4) Intruder target attraction: A function that will ensure that the intruder is attracted towards its target is defined as:

$$B(\boldsymbol{x}) := \frac{1}{2}\|\boldsymbol{x} - \boldsymbol{x}_\tau\|^2. \tag{9}$$

5) Collision avoidance between the intruder and the ith swarm individual: As the intruder will try to approach its target, it will encounter swarm individuals, which will try to capture or stop the intruder. The intruder would perform the collision avoidance maneuvers and not by the individuals of the swarm. A one-way avoidance scheme will be created. An avoidance function to avoid the intruder from colliding with the individuals is defined as follows:

$$D_i(\mathbf{x}) := \frac{1}{2}\left[\|\boldsymbol{x} - \boldsymbol{x}_i\|^2 - (r_a + r_b)^2\right]. \tag{10}$$

B. A Lyapunov Function

Let there be positive real numbers $\alpha, \gamma_i, \beta_{ij}, \epsilon, \eta_i$ for $i, j \in \{1, 2, 3, \ldots, n\}$ and $j \neq i$. A Lyapunov function suitable for system (4) is of the form

$$\begin{aligned} L(\mathbf{x}) &= T(\mathbf{x})\left(\alpha + \sum_{i=1}^{n}\left(\gamma_i R_i(\boldsymbol{x}_i) + \sum_{\substack{j=1,\\ j\neq i}}^{n}\frac{\beta_{ij}}{Q_{ij}(\boldsymbol{x}_i)}\right)\right) \\ &\quad + T(\mathbf{x})\left(\sum_{i=1}^{n}\frac{\eta_i}{D_i(\mathbf{x})} + \epsilon B(\boldsymbol{x})\right) \end{aligned} \tag{11}$$

C. Velocity Controllers

Along a trajectory of the swarm system (4), we have

$$\dot{L}(\mathbf{x}) = \sum_{i=1}^{n}\left[f_i(\mathbf{x})\dot{x}_i + g_i(\mathbf{x})\dot{y}_i\right] + p(\mathbf{x})\dot{x} + q(\mathbf{x})\dot{y}, \tag{12}$$

where

$$f_i(\mathbf{x}) = \frac{\partial L(\mathbf{x})}{\partial x_i}, \tag{13}$$

$$g_i(\mathbf{x}) = \frac{\partial L(\mathbf{x})}{\partial y_i}, \tag{14}$$

$$p(\mathbf{x}) = \frac{\partial L(\mathbf{x})}{\partial x}, \tag{15}$$

and

$$q(\mathbf{x}) = \frac{\partial L(\mathbf{x})}{\partial y}. \tag{16}$$

Let there be scalars $\mu_i > 0$, $\varphi_i > 0$, $\Omega > 0$ and $\mho > 0$. Then the velocity controllers of system (4) are

$$\left.\begin{aligned} v_i &= -\mu_i f_i(\mathbf{x}), \\ w_i &= -\varphi_i g_i(\mathbf{x}), \\ \sigma &= -\Omega p(\mathbf{x}), \\ \delta &= -\mho q(\mathbf{x}). \end{aligned}\right\} \tag{17}$$

VI. Stability Analysis

It is evident that $L(\mathbf{x})$ is positive over the domain

$$\begin{aligned} D\big(L(\mathbf{x})\big) &:= \Big\{\mathbf{x} \in \mathbb{R}^{2n+2} : Q_{ij}(\mathbf{x}) > 0, D_i(\mathbf{x}) > 0, \\ &\qquad \forall\, i, j = \{1, 2, 3, \ldots, n\}, i \neq j\Big\}. \end{aligned}$$

Substituting (17) into (12) gives

$$\begin{aligned} \dot{L}(\mathbf{x}) &= -\left(\sum_{i=1}^{n}\left[\mu_i f_i(\mathbf{x}) + \varphi_i g_i(\mathbf{x})\right] + \Omega p(\mathbf{x}) + \mho q(\mathbf{x})\right) \\ &\leq 0, \end{aligned}$$

$\forall \mathbf{x} \in D\big(L(\mathbf{x})\big)$. At the equilibrium point, $\mathbf{x}_e$, where $\boldsymbol{x}_C = \boldsymbol{x}$, the instantaneous velocities, v_i, w_i, σ and δ are zero because $f_i(\mathbf{x}) = g_i(\mathbf{x}) = p(\mathbf{x}) = q(\mathbf{x}) = 0$, that is, $L(\mathbf{x}_e) = 0$.

VII. Simulation Results

Simulations were generated using Wolfram Mathematica 12.1 software. To achieve the desired results, Mathematica commands were executed, meaning that the Mathematica commands were based on the Lyapunov components, Lyapunov function, and velocity controllers of our swarm intruder system (4). The positions of the swarm individuals were randomly generated. The initial and target positions of the intruder were assigned. System (4) was numerically simulated using RK4 method (Runge-Kutta Method).

Example 7.1: The initial positions of a swarm of 10 individuals with the initial position and target location of a moving target (intruder) is shown in Fig. 2. The swarm individuals clusters around the centroid as time evolves and then moves towards the moving target as a well-spaced cohesive group and eventually captures the intruder, as shown in Fig. 3. Fig. 4 shows the evolution of $L(\mathbf{x})$ and its derivative with respect to time. Distance between the centroid of the swarm and the moving target (intruder) is shown in Fig. 5. Snap shots taken in Region A (which is present in Fig. 3) are shown in Fig. 6.

VIII. Conclusion

This paper presents stabilizing nonlinear time-invariant continuous velocity-based control laws derived from LbCS of a swarm of $n \in \mathbb{N}$ individuals and a intruder. The control laws enable a swarm of $n \in \mathbb{N}$ individuals to navigate from their initial configuration to capture a moving target (intruder). The effectiveness of the controllers were validated through computer simulation. Interaction of the three main pillars of LbCS, which are safety, shortness, and smoothest path for motion planning, bring about cost and time effectiveness and efficiency of the velocity controllers. This paper is a theoretical exposition into the applicability of LbCS, and we have restricted ourselves to showing the effectiveness of velocity-based control laws using computer-based simulation of a scenario and numerical proof. It is feasible for the industry sector to include such controllers for the development of autonomous mobile robots. Development of such technologies for security measures will definitely assist in apprehending intruders.

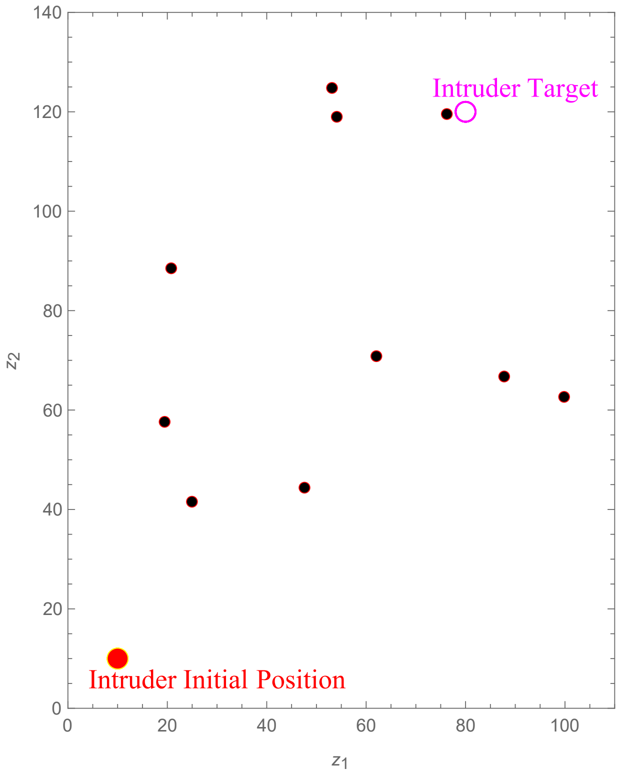


Fig. 2. Initial Positions.

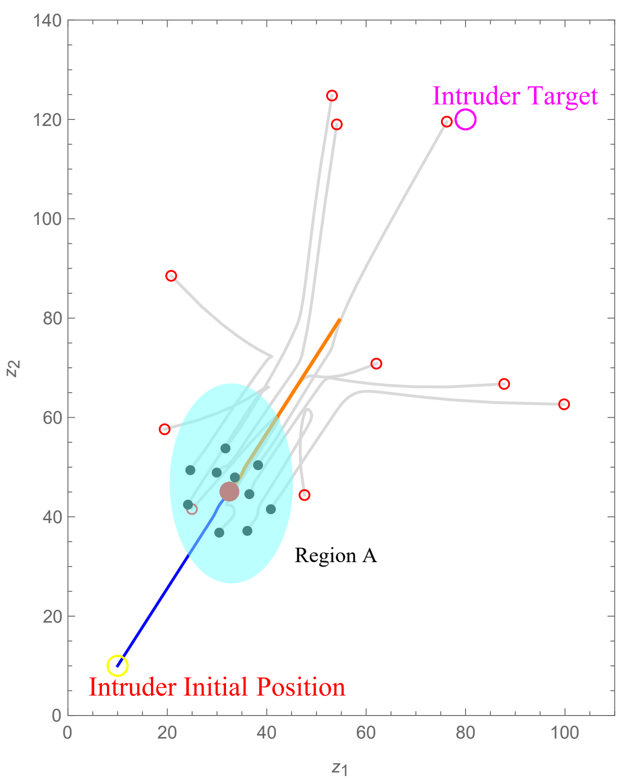


Fig. 3. Final Positions. For this result, $\alpha = 0.5, \gamma_i = 0.3, \beta_{ij} = 10, \eta_i = 2, \epsilon = 0.001, \mu_i = \varphi_i = 0.001$, and $\Omega = \mho = 0.0001$.

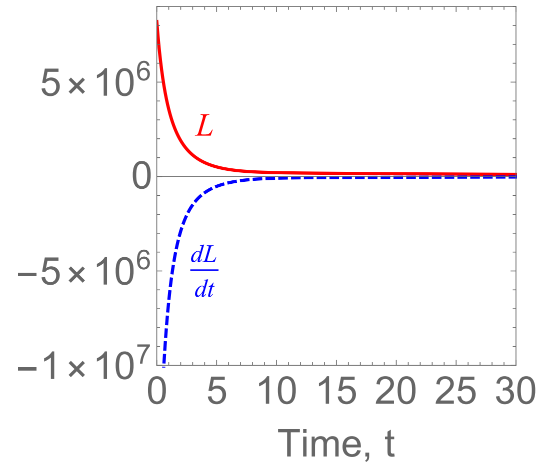


Fig. 4. Monotonically decreasing Lyapunov function and its time derivative.

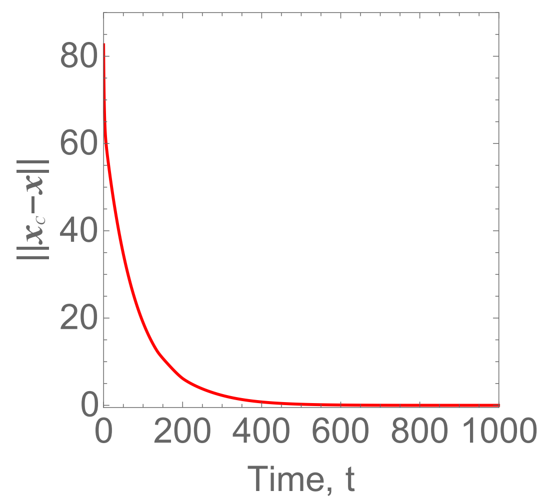
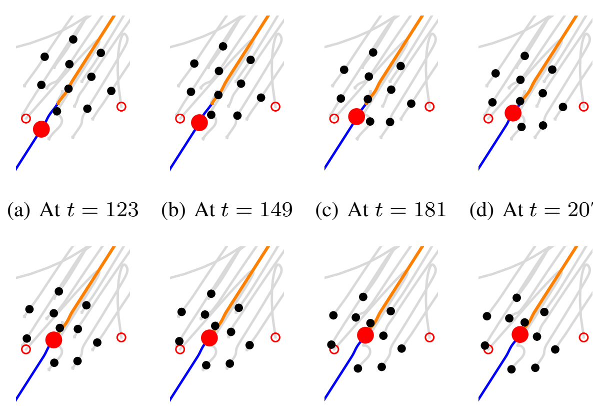


Fig. 5. Distance between the centroid of the swarm and the intruder.



(a) At $t = 123$ (b) At $t = 149$ (c) At $t = 181$ (d) At $t = 207$

(e) At $t = 260$ (f) At $t = 302$ (g) At $t = 413$ (h) At $t = 498$

Fig. 6. Images taken at $t = 123, 149, 181, 207, 260, 302, 413$, and 498, respectively, show the self-organization of the individuals in Region A as shown in Figure 3.

The future work will consider combining the current algorithm, however, to one of the heuristic-based approaches to form a hybrid system, which inherits the benefits of LbCS but can flush out local minima using the latter approach.

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REFERENCES

[1] J. Vanualailai. Stable emergent formations for a swarm of autonomous car-like vehicles. *International Journal of Advanced Robotic Systems*, 16(5):1729881419849780, 2019.
[2] T. Fukuda and S. Nakagawa. Approach to the dynamically reconfigurable robotic system. *J Intell Robot Syst*, 1:55–72, 1988.
[3] P. Tosato, D. Facinelli, M. Prada, L. Gemma, M. Rossi, and D. Brunelli. An autonomous swarm of drones for industrial gas sensing applications. In *2019 IEEE 20th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, pages 1–6, 2019.
[4] H. Ahmed and J. Glasgow. Swarm intelligence : Concepts , models and applications technical report 2012-585. 2012.
[5] J. Vanualailai, A. Sharan, and B. Sharma. A swarm model for planar formations of multiple autonomous unmanned aerial vehicles. In *2013 IEEE International Symposium on Intelligent Control (ISIC)*, pages 206–211, 2013.
[6] S. A. Kumar, J. Vanualailai, B. Sharma, and A. Prasad. Velocity controllers for a swarm of unmanned aerial vehicles. *Journal of Industrial Information Integration*, 22:100198, 2021.
[7] S. A. Kumar, J. Vanualailai, and B. Sharma. Lyapunov functions for a planar swarm model with application to nonholonomic planar vehicles. In *2015 IEEE Conference on Control Applications (CCA)*, pages 1919–1924, 2015.
[8] B. N. Sharma, J. Raj, and J. Vanualailai. Navigation of carlike robots in an extended dynamic environment with swarm avoidance. *International Journal of Robust and Nonlinear Control*, 28(2):678–698, 2018.
[9] S. A. Kumar and J. Vanualailai. A Lagrangian UAV swarm formation suitable for monitoring exclusive economic zone and for search and rescue. In *Proceedings of the 2017 IEEE Conference on Control Technology and Applications*, pages 1874–1879, Kohala Coast, Hawai'i, USA, August 2017.
[10] A. Devi, J. Vanualailai, S. A. Kumar, and B. Sharma. A cohesive and well-spaced swarm with application to unmanned aerial vehicles. In *Proceedings of the 2017 International Conference on Unmanned Aircraft Systems*, pages 698–705, Miami, FL, USA, June 2017.
[11] S. A. Kumar, J. Vanualailai, and B. Sharma. Emergent formations of a Lagrangian swarm of unmanned ground vehicles. In *Proceedings of the 14th International Conference on Control, Automation, Robotics and Vision*, Phuket, Thailand, November 2016.
[12] S. A. Kumar, J. Vanualailai, and B. Sharma. Lyapunov-based control for a swarm of planar nonholonomic vehicles. *Mathematics in Computer Science*, 9(4):461–475, October 2015.
[13] S. A. Kumar, B. Sharma, J. Vanualailai, and A. Prasad. Stable switched controllers for a swarm of UGVs for hierarchal landmark navigation. *Swarm and Evolutionary Computation*, 65:100926, 2021.
[14] J. Kennedy. *Swarm Intelligence*, pages 187–219. Springer US, Boston, MA, 2006.
[15] C.N. Onyishi, M.O. Ede, O.V. Ossai, and C.S. Ugwuanyi. Rational emotive occupational health coaching in the management of police subjective well-being and work ability: a case of repeated measures. *J Police Crim Psych*, 36:96–111, 2021.
[16] A. Prasad, B. Sharma, and J. Vanualailai. A new stabilizing solution for motion planning and control of multiple robots. *Robotica*, 34(5):10711089, 2016.
[17] B. Sharma, J. Vanualailai, and S. Singh. Motion planning and posture control of multiple n-link doubly nonholonomic manipulators. *Robotica*, 35(1):125, 2017.
[18] Y. Tan and Z. Zheng. Research advance in swarm robotics. *Defence Technology*, 9(1):18–39, 2013.
[19] E. Bonabeau and C. Meyer. Swarm intelligence. a whole new way to think about business. *Harvard business review*, 79 5:106–14, 165, 2001.
[20] A. Okubo and S.A. Levin. *Diffusion and Ecological Problems: Modern Perspectives*. Interdisciplinary Applied Mathematics. Springer, 2001.
[21] S. Yang and Y. Sato. Swarm intelligence algorithm based on competitive predators with dynamic virtual teams. *Journal of Artificial Intelligence and Soft Computing Research*, 7(2):87–101, 2017.
[22] A. Silva, A. Neves, and E. Costa. An empirical comparison of particle swarm and predator prey optimisation. In *Proceedings of the 13th Irish International Conference on Artificial Intelligence and Cognitive Science*, AICS '02, page 103110, Berlin, Heidelberg, 2002. Springer-Verlag.
[23] H. Duan, S. Li, and Y. Shi. Predatorprey brain storm optimization for dc brushless motor. *IEEE Transactions on Magnetics*, 49(10):5336–5340, 2013.
[24] V. Gazi and K. M. Passino. Stability analysis of social foraging swarms. *IEEE Transactions on Systems, Man and Cybernetics – Part B*, 34(1):539–557, 2004.
[25] K. Jin, P. Liang, and G. Beni. Stability of synchronized distributed control of discrete swarm structures. In *Proceedings of the 1994 IEEE International Conference on Robotics and Automation*, pages 1033–1038 vol.2, 1994.
[26] G. Beni and Ping Liang. Pattern reconfiguration in swarms-convergence of a distributed asynchronous and bounded iterative algorithm. *IEEE Transactions on Robotics and Automation*, 12(3):485–490, 1996.
[27] S. A. Kumar, J. Vanualailai, and A. Prasad. Distributed velocity controllers of the individuals of emerging swarm clusters. In *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, pages 1–6, 2020.
[28] V. Chand, A. Prasad, K. Chaudhary, B. Sharma, and S. Chand. A face-off-classical and heuristic-based path planning approaches. In *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, pages 1–6, 2020.
[29] B. Sharma, J. Vanualailai, and S. Singh. Lyapunov-based nonlinear controllers for obstacle avoidance with a planar n-link doubly nonholonomic manipulator. *Robotics and Autonomous Systems*, 60(12):1484–1497, 2012.
[30] J. Raj, K. Raghuwaiya, S. Singh, B. Sharma, and J. Vanualailai. Swarming intelligence of 1-trailer systems. In Hamzah Asyrani Sulaiman, Mohd Azlishah Othman, Mohd Fairuz Iskandar Othman, Yahaya Abd Rahim, and Naim Che Pee, editors, *Advanced Computer and Communication Engineering Technology*, pages 251–264, Cham, 2016. Springer International Publishing.
[31] J. Raj, K. Raghuwaiya, J. Vanualailai, and B. Sharma. Navigation of car-like robots in three-dimensional space. In *2018 5th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE)*, pages 271–275, 2018.
[32] Sandeep A. Kumar, , J. Vanualailai, and A. Prasad. Assistive technology: autonomous wheelchair in obstacle-ridden environment. *PeerJ Computer Science*, 7:e725:1–23, 2021.
[33] B. Sharma, J. Vanualailai, and S. Singh. Tunnel passing maneuvers of prescribed formations. *International Journal of Robust and Nonlinear Control*, 24(5):876–901, 2014.
[34] B. Sharma, J. Vanualailai, and S. Singh. Motion planning and posture control of multiple n-link doubly nonholonomic manipulators. *Robotica*, 35:1–25, March 2015.
[35] A. Prasad, B. Sharma, J. Vanualailai, and S. Kumar. Motion control of an articulated mobile manipulator in 3D using the Lyapunov-based control scheme. *International Journal of Control*, pages 1–15, 2021.
[36] B. Sharma, J. Vanualailai, and A. Prasad. Formation control of a swarm of mobile manipulators. *The Rocky Mountain Journal of Mathematics*, pages 909–940, 2011.
[37] K. Raghuwaiya, J. Vanualailai, and B. Sharma. Formation splitting and merging. In Ying Tan, Yuhui Shi, and Li Li, editors, *Advances in Swarm Intelligence*, pages 461–469, Cham, 2016. Springer International Publishing.
[38] B. Sharma, J. Vanualailai, and S. Singh. Lyapunov-based nonlinear controllers for obstacle avoidance with a planar n-link doubly nonholonomic manipulator. 60(12), 2012.
[39] B. Sharma, S. Singh, J. Vanualailai, and A. Prasad. Globally rigid formation of n-link doubly nonholonomic mobile manipulators. *Robotics and Autonomous Systems*, 105:69–84, 2018.