



APPLICATION OF FUZZY LOGIC IN COLLISION AVOIDANCE CONTROL OF MULTIPLE SWARM ROBOTS

Le Thi Thuy Nga*, Nguyen Manh Dung

University of Transport and Communications, No 3 Cau Giay Street, Hanoi, Vietnam

ARTICLE INFO

TYPE: Research Article

Received: 10/01/2026

Revised: 19/03/2026

Accepted: 26/03/2026

Published online: 15/05/2026

<https://doi.org/10.47869/tcsj.77.4.9>

* Corresponding author

Email: lethuynga@utc.edu.vn; Tel: 0987065998

Abstract. In nature, many swarms of organisms may encounter one another while moving in search of food, which can lead to conflicts between groups. In the field of transportation, there are flows of unmanned vehicles traveling from different directions on the roads; when they reach intersections, the challenge is how these vehicles can pass one another without collisions and then continue toward their destinations as originally planned. Groups of drones fly in the sky, controlled to form various shapes. So how do these drone swarms move past each other without colliding while forming the desired shape? This paper proposes a solution based on the use of Takagi–Sugeno and Mamdani SISO fuzzy structures to compute internal forces within a swarm, target-directed forces, and forces for avoiding other swarms. The proposals above will be validated through MATLAB simulations under different scenarios involving varying numbers of swarms and different numbers of individuals in each swarm.

Keywords: swarm robots, multiple swarm robots, collision avoidance, swarms maintain, Takagi–Sugeno fuzzy structures, Mamdani fuzzy structures.

© 2026 University of Transport and Communications

1. INTRODUCTION

Swarm robotics is an emerging research trend with strong potential in the field of robotic technology. Due to its characteristics of high intelligence without requiring complex manufacturing technologies, swarm robotics has attracted increasing research interest. However, each project has its own research objectives. Swarm motion is one of the most extensively studied problems in swarm robotics based on well-established biological foundations. In the flocking of birds, each bird flies independently within the flock without

considering the overall formation of the flock. However, when observing the entire shape of the flock, it appears as if all the birds have agreed on a common movement plan. Thousands of birds can bond together into a group, move collectively, and respond rapidly to encountered obstacles. In 1987, Reynolds [1] was the first to simulate flocking behavior using his own program. In 1996, Kelly and Keating [2] demonstrated flocking behavior using 5 small-sized robots. Each robot was equipped with an ultrasonic sensor to detect obstacles, along with an infrared sensor system to exchange information among robots and determine their positions. Swarm motion consists of 4 levels of control: obstacle avoidance; if no individual is detected in front, the robot becomes the leader and flashes; if it is within the swarm, it maintains its position; and if the leader is detected, it increases speed and moves toward it. The selection of the leader is flexible, and all will move in a swarm; when encountering obstacles, the swarm can split into two smaller swarms and then merge back into one after passing the obstacle. In 2007, Hanada [3] suggested a strategy to extend swarm robotics, allowing robots to move autonomously in environments with multiple obstacles. Each robot independently selects two neighboring robots and maintains a certain distance from them using sensors, then performs movements allowing the swarm to divide into multiple groups when encountering obstacles and to reunite into a unified formation after overcoming the obstacles. They showed that an adaptive flocking algorithm, based on local interactions among robots, allows the swarm to navigate autonomously in environments with many obstacles. Nga L.T.T. and colleagues [4,5,6,7] addressed the problem of swarm robot control for target searching in environments with multiple static obstacles based on fuzzy logic and null-space-based behavior. The results demonstrated that the individual robots in the swarm were able to accomplish the assigned tasks. Kohei Yamagishi and Tsuyoshi Suzuki [8] mentioned the movement of multiple robot swarms within the same environment with the objective that the swarms pass through each other cooperatively at their intersections under decentralized control. This study proposed adjusting turning behavior based on chaos theory to ensure that robot swarms avoid collisions with other approaching swarms. After passing other swarms, they continue their collective motion task. In [9], Gaurav Kumar and colleagues proposed a hybrid solution combining chaos theory and the Dragonfly Algorithm (DA) to maximize the spatial coverage of swarm robots. The results showed that this solution was more effective than the previously studied CBA (Chaotic Bat Algorithm) and CAPSO (Chaotic Accelerated Particle Swarm Optimization). In addition, robot groups are required to exhibit avoidance behaviors to allow other robot groups to pass through without disrupting their formation, as discussed in the studies by Y. Yaguchi and K. Tamagawa [10], as well as methods for passing through the spaces within another robot swarm as presented in the studies by B. Zhang and H. P. Gavin [11] and L. Luo et al. [12]. These methods are controlled based on comprehensive information and robot state information without considering the formation of the swarm. For example, in cooperative transport tasks involving multiple robot swarms, each swarm must maintain its formation under decentralized control, and it is necessary to develop local collision avoidance methods when the swarms approach one another.

An analysis of the above studies shows that controlling robot swarms with different formations and scales in environments where multiple swarms move simultaneously is still very limited, whereas in practice, there are many situations in which collisions between groups of individuals occur. For example, in the fields of railways, road transportation, and logistics, there are flows of unmanned vehicles traveling from different directions; when they reach intersections, the question is how these vehicles can pass one another without collisions and then continue toward their destinations as originally planned. Another typical example of this

problem is groups of drones flying in the sky, which are controlled to form different patterns or images. During movement, collisions may occur between groups; thus, the question is how drone swarms can pass through one another without colliding, so that they can form the desired patterns.

Based on the above practical requirements, this paper focuses on addressing the collision avoidance problem of robot swarms in environments with potential conflicts, under the condition that the swarms maintain their formations and, after avoiding one another, continue performing their ongoing tasks. The paper presents the mathematical model of swarm robots, followed by the application of fuzzy logic to determine the forces acting on each individual robot and the interaction forces between swarms when moving in conflict-prone environments. Finally, simulation results using MATLAB software are provided to illustrate the movement process of multiple robot swarms within the same environment.

2. THE TOTAL FORCE ACTING ON THE SWARM ROBOT

2.1. Dynamic model of the swarm robots

Consider a swarm consisting of N robots, assuming the robots are point particles and their size is ignored. Then the motion of the i -th robot ($i=1 \div N$) in an n -dimensional space is represented by the following system of equations:

$$\dot{p}_i = f_i \tag{1}$$

where: $p_i = \begin{bmatrix} p_i^1 \\ p_i^2 \\ \vdots \\ p_i^n \end{bmatrix}$ $v_i = \begin{bmatrix} v_i^1 \\ v_i^2 \\ \vdots \\ v_i^n \end{bmatrix}$ respectively denote the position and velocity of the i -th robot,

and f_i is the sum of all forces acting on the i -th robot.

Equation (1) can be expressed in a discrete-time form as follows:

$$\begin{cases} v_i[T+1] = f_i[T+1] \\ p_i[T+1] = p_i[T] + v_i[T+1]\Delta t \end{cases} \tag{2}$$

where: T is the computation step, Δt is the time step length. If T_C denotes the total number of computation steps, then $T=1 \div T_C-1$.

When a robot swarm moves in an environment with more than one swarm to search for a target, each robot in the swarm is subjected to the following forces:

- The interaction force among robots within the same swarm, referred to as the internal force f_i^{int} .
- The target-directed force f_i^{goal} .
- The avoidance force with respect to other swarms f_i^{swarm} .

Therefore, the total force acting on the i -th robot is given by:

$$f_i = f_i^{int} + f_i^{goal} + f_i^{swarm} \tag{3}$$

2.2 Determination of Forces Acting on the Swarm Robot

2.2.1 Determination of Internal Forces in the Swarm Robot

To maintain the structure of the swarm, the distance between individual robots within the swarm must remain stable. If we denote σ_s , σ_s^* respectively, the actual distance and the desired (stable) distance between the pair of individuals (i,j) with $j=1 \div N$ and $j \neq i$, then the objective of maintaining the swarm formation is therefore $\sigma_s = \sigma_s^*$. In an n-dimensional space, the Euclidean distance between robots i and j is defined by the following formula:

$$\sigma_s = \|p_i - p_j\| = \sqrt{(p_i^1 - p_j^1)^2 + (p_i^2 - p_j^2)^2 + \dots + (p_i^n - p_j^n)^2} \quad (4)$$

The interaction force between each pair of individuals (i, j) denoted as f_{ij}^{int} depends on the difference between the actual distance and the desired distance $e^{int} = \sigma_s - \sigma_s^*$, if $e^{int} > 0$ then f_{ij}^{int} is referred to as an attractive force; if $e^{int} < 0$ then f_{ij}^{int} is referred to as a repulsive force; if $e^{int} = 0$ then $f_{ij}^{int} = 0$. The more positive e^{int} is, the stronger the attractive force, the more negative e^{int} is, the stronger the repulsive force. Therefore, a Takagi–Sugeno fuzzy system with a SISO structure can be used to compute the force f_{ij}^{int} as follows:

- The input signal is $u = e^{int}$ whose domain is the interval of $[\alpha_b, \beta_b] \in \mathbb{R}$, and it is divided into $2K+1$, intervals B^k as illustrated in Figure 1.

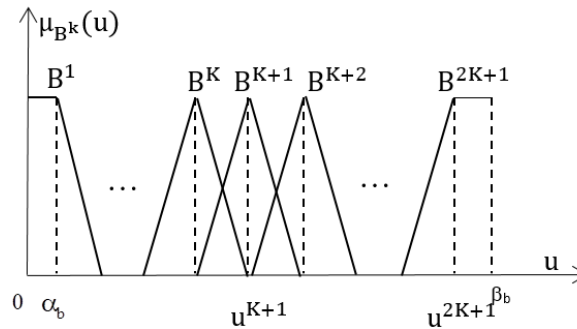


Figure 1. Fuzzification of the input signal u.

- The output signal is $A = f_{ij}^{int} = f(u)$, whose domain lies in the interval $[\alpha_a, \beta_a]$, dividing A into $2K+1$ intervals A^k with $k = 1, 2, \dots, 2K+1$ as shown in Figure 2, the centroid a^k of the fuzzy interval A^k is:

$$a^k \begin{cases} < 0, k = 1 \div K \\ = 0, k = K + 1 \\ > 0, k = K + 2 \div 2K + 1 \end{cases} \quad (5)$$

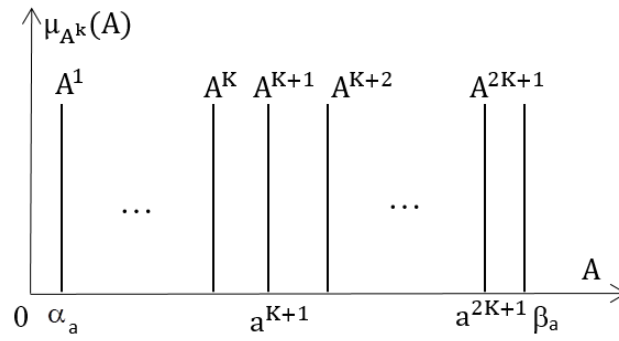


Figure 2. Fuzzification of the output signal $f(u)$.

Establish $2K+1$, If... Then... rules in the following form: If $u = B^k$ Then $a=A^k$, where A^k is a constant.

- The composition rule is selected, and defuzzification is performed using the weighted average method:

$$f(u) = \frac{\sum_{k=1}^{2K+1} a^k \mu_{B^k}(u)}{\sum_{k=1}^{2K+1} \mu_{B^k}(u)} \quad (6)$$

The fuzzy function $f(u)$ is a continuous function satisfying the following conditions:

- Upper and lower limits: $a^1 \leq f(u) \leq a^{2K+1}$
- Segment linearization equation:

$$f(u) = \frac{(a^{k+1} - a^k)u + a^k u^{k+1} - a^{k+1} u^k}{u^{k+1} - u^k}$$

When moving, each robot is influenced by all other robots in the swarm; therefore, the internal force acting on the i -th robot is f_i^{int} determined by the formula:

$$f_i^{int} = \sum_{j=1, j \neq i}^N f_{ij}^{int} \quad (7)$$

2.2.2. Determination of the Target-Directed Force

Assume that the target has coordinates $p_{goal} = \begin{bmatrix} p_g^1 \\ p_g^2 \\ \vdots \\ p_g^n \end{bmatrix}$ in an n -dimensional space, the

Euclidean distance from the i -th robot to the target is then determined by the following formula:

$$\sigma_{goal} = \|p_i - p_{goal}\| = \sqrt{(p_i^1 - p_g^1)^2 + (p_i^2 - p_g^2)^2 + \dots + (p_i^n - p_g^n)^2} \quad (8)$$

The target-directed force of the robots in the swarm depends on the distance from the robot to the target; the greater the distance σ_{goal} , the larger the force f_i^{goal} . A Mamdani fuzzy system with a SISO structure can be used to compute the force f_i^{goal} , specifically as follows:

- The input signal is $u_{goal} = \sigma_{goal}$ whose domain is the interval of $[\alpha_{bgoal}=0, \beta_{bgoal}]$, and it is divided into $K1$, intervals B^{goalk1} as illustrated in Figure 3.

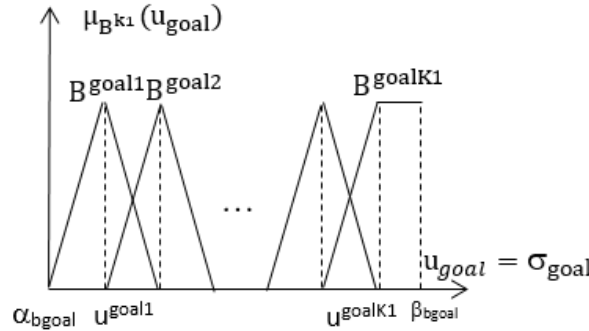


Figure 3. Fuzzification of the input signal u_{goal} .

- The output signal is $A_{goal} = f_i^{goal}$, whose domain lies in the interval $[\alpha_{agoal}=0, \beta_{agoal}]$, dividing A_{goal} into $K1$ intervals A^{goalk1} with $k = 1, 2, \dots, K1$ as shown in Figure 4.

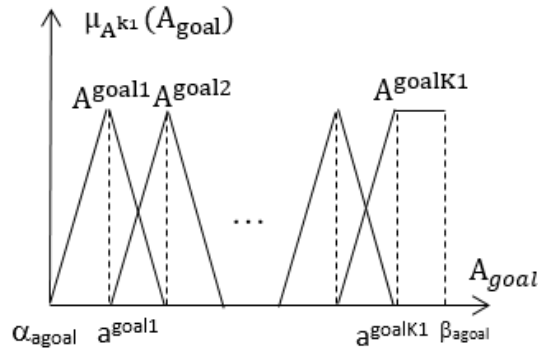


Figure 4. Fuzzification of the output signal A_{goal} .

Establish $K1$, If... Then... rules in the following form: If $u_{goal} = B^{goalk1}$ Then $[0, \beta]$

- The composition rule is selected, and defuzzification is performed using the weighted average method:

$$f(u_{goal}) = \frac{\sum_{k1=1}^{K1} a^{goalk1} \mu_{B^{goalk1}}(u_{goal})}{\sum_{k1=1}^{K1} \mu_{B^{goalk1}}(u_{goal})} \quad (9)$$

2.2.3. Determine the Force Required to Avoid Other Swarms

When multiple robot swarms move within the same environment, conflicts are likely to occur, as the swarms may collide with one another, which requires establishing a collision avoidance mechanism among robot swarms.

Assume that there are N_s swarms in the environment. Denote $p_{C_s} = \begin{bmatrix} p_{C_s}^1 \\ p_{C_s}^2 \\ \vdots \\ p_{C_s}^n \end{bmatrix}$ the centroid

position of a robot swarm consisting of N individual robots; the swarm centroid is then determined as follows:

$$\begin{cases} p_{C_s}^1 = \frac{1}{N} \sum_{i=1}^N p_i^1 \\ p_{C_s}^2 = \frac{1}{N} \sum_{i=1}^N p_i^2 \\ \vdots \\ p_{C_s}^n = \frac{1}{N} \sum_{i=1}^N p_i^n \end{cases} \quad (10)$$

The distance from the swarm centroid p_{C_s} to the position of the i -th robot in the swarm is determined by the following formula:

$$\sigma_{iC_s} = \|p_i - p_{C_s}\| = \sqrt{(p_i^1 - p_{C_s}^1)^2 + (p_i^2 - p_{C_s}^2)^2 + \dots + (p_i^n - p_{C_s}^n)^2} \quad (11)$$

Let R_{C_s} denote the radius of the robot swarm; then R_{C_s} is the distance from the centroid p_{C_s} to the farthest robot in the swarm:

$$R_{C_s} = \max_{i=1 \div N} (\sigma_{iC_s}) \quad (12)$$

The Euclidean distance between the centroids of swarm C_{si} and swarm C_{sj} with $C_{sj} \neq C_{si}$ and ($C_{si}, C_{sj}=1 \div N_s$):

$$\sigma_{C_{si}C_{sj}} = \|p_{C_{si}} - p_{C_{sj}}\| = \sqrt{(p_{C_{si}}^1 - p_{C_{sj}}^1)^2 + (p_{C_{si}}^2 - p_{C_{sj}}^2)^2 + \dots + (p_{C_{si}}^n - p_{C_{sj}}^n)^2} \quad (13)$$

The effective distance between the two swarms is then defined as:

$$d_{C_{si}C_{sj}} = \sigma_{C_{si}C_{sj}} - (R_{C_{si}} - R_{C_{sj}}) \quad (14)$$

The interaction force between two swarms depends on the effective distance between two swarms $d_{C_{si}C_{sj}}$, and a fuzzy set with Mamdani – SISO structure can be used to compute this interaction force:

- The input signal is $u_s = d_{C_{si}C_{sj}} - d_{C_{si}C_{sj}}^*$ whose domain is the interval of $[\alpha_{bs}, \beta_{bs}=0]$, and it is divided into K_2 , intervals B^{sk_2} as illustrated in Figure 5.

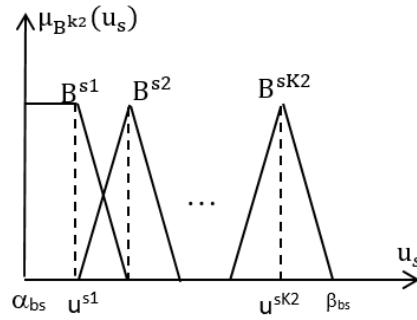


Figure 5. Fuzzification of the input signal u_s .

- The output signal is $A_s = f_{CsiCsj}$, whose domain lies in the interval $[\alpha_{as}, \beta_{as}=0]$, dividing A_s into K_2 intervals A^{sk2} with $k_2 = 1, 2, \dots, K_2$ as shown in Figure 6.

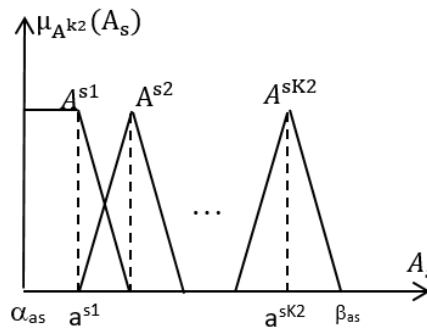


Figure 6. Fuzzification of the output signal A_s .

Establish K_2 , If... Then... rules in the following form: If $u_s = B^{sk2}$ Then $A_s = A^{sk2}$.

- The composition rule is selected, and defuzzification is performed using the weighted average method:

$$f_{CsiCsj} = f(u_s) = \frac{\sum_{k_2=1}^{K_2} a^{sk2} \mu_{B^{sk2}}(u_s)}{\sum_{k_2=1}^{K_2} \mu_{B^{sk2}}(u_s)} \quad (15)$$

The unit normal vector of swarm C_{si} with respect to swarm C_{sj} directed from the centroid of swarm C_{sj} to the centroid of swarm C_{si} , is used to determine the direct repulsive direction in order to increase the distance between the two swarms when there is a risk of collision:

$$n_{CsiCsj} = \frac{p_{Csi} - p_{Csj}}{\sigma_{CsiCsj}} \quad (16)$$

The unit tangential vector t_{CsiCsj} is perpendicular to the vector n_{CsiCsj} .

The C_{si} swarm's avoidance force against the C_{sj} swarm:

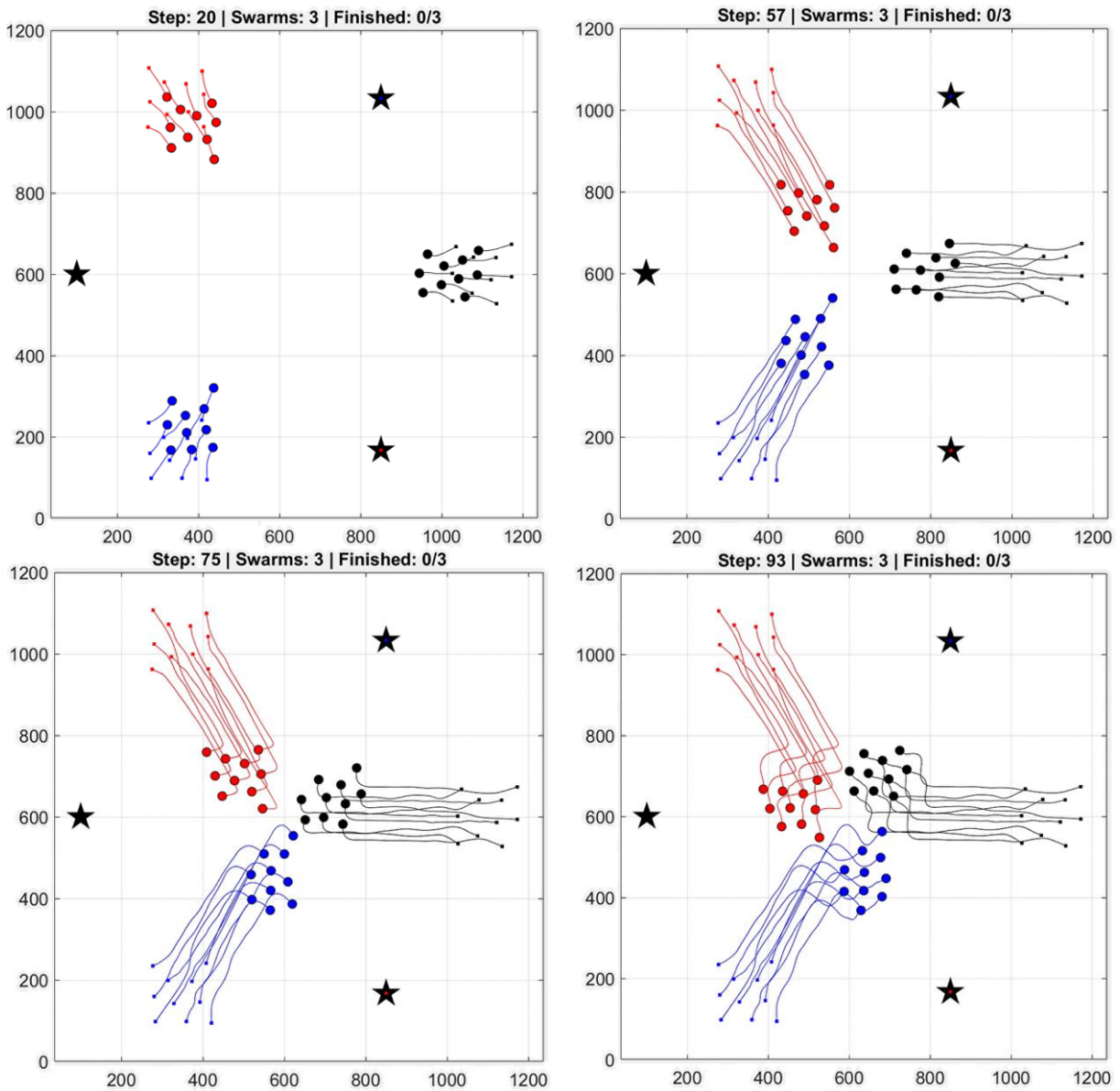
$$f_{CsiCsj}^{swarm} = f_{CsiCsj} (n_{CsiCsj} + t_{CsiCsj}) \quad (17)$$

When multiple robot swarms move within the same environment, each swarm is affected by the remaining N_s-1 swarms, therefore, the total inter-swarm avoidance force is:

$$f_i^{swarm} = \sum_{Csj=1, Csj \neq Csi}^{Ns} f_{CsiCsj}^{swarm} \quad (18)$$

3. SIMULATION RESULT

The simulation environment is assumed to be an n=2-dimensional space with dimensions [1200 1200]. The number of swarms and the number of robot individuals in each swarm are arbitrary. The initial positions of the robots are denoted by the symbol “■”, the final positions by the symbol “●”, and the target by the five-pointed star symbol “★”. The process of swarm movement toward the target is illustrated in Figures 7 and 8.



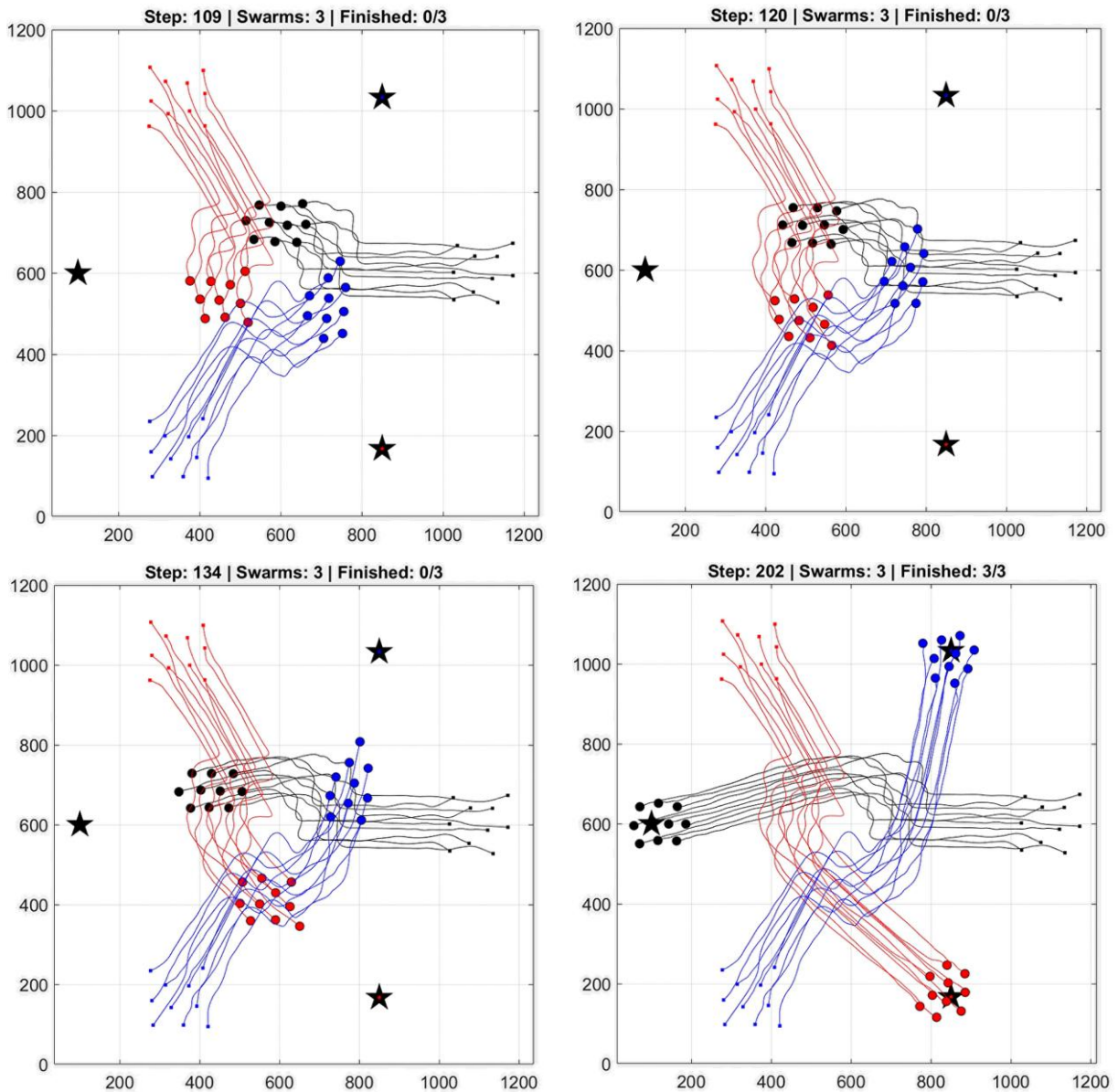


Figure 7. The movement process of the three robot swarms at different times.

Figure 7 shows that during movement, the robots belonging to the swarms always move together, towards the same target and avoiding other swarms.

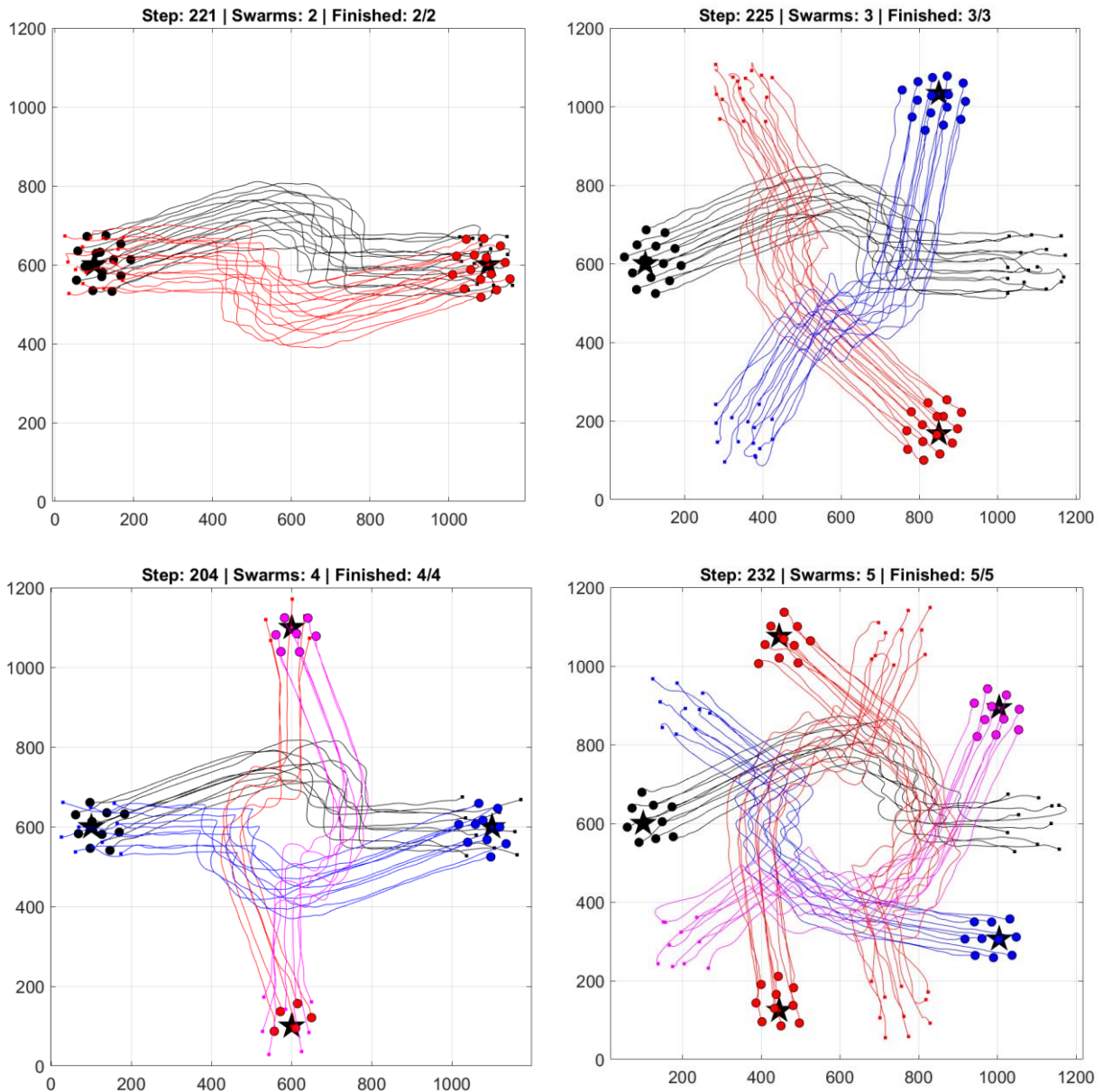


Figure 8. The movement process of robot swarms with varying numbers of swarms.

The simulation results shown in Figures 7 and 8 demonstrate that the robot swarms are capable of moving toward the target while continuously maintaining their formations. At locations with potential conflicts, the swarms successfully avoid one another, thereby preventing collisions.

4. CONCLUSION

The solution using fuzzy logic to compute the forces, including the interaction force among robots within the same swarm, the repulsive force between different robot swarms, and the attractive force between individual robots and the target, enables the swarms to avoid one another while preserving their formations in environments with a risk of collision. After avoiding other swarms, the swarms continue performing their target-searching tasks.

ACKNOWLEDGMENT

This research is funded by University of Transport and Communications (UTC) under grant number T2025-DT-003TD.

REFERENCES

- [1]. C.W. Reynolds, Flocks, Herds, and Schools: A Distributed Behavioral Model - Symbolics Graphics Division, Published in Computer Graphics, 21(1987) 25-34.
- [2]. I. D.Kelly, D.A. Keating, Flocking by the fusion of sonar and active infrared sensors on physical autonomous mobile robots, Proc. Mechatronics '96, 1996.
- [3]. Hanada, Y. G. Lee, N. Y. Chong, Adaptive Flocking of a Swarm of Robots Based on Local Interactions, Sch. of Inf. Sci., Japan Adv. Inst. of Sci. & Technol, Nomi Swarm Intelligence Symposium, (2007) 340-347.
- [4]. Lê Thị Thúy Nga, Lê Hùng Lân, Phân tích sự ổn định tụ bầy của robot bầy đàn sử dụng hàm hút/đẩy mờ, Tạp chí Khoa học Giao thông Vận tải, 10 (2013) 88-93.
- [5]. Lê Thị Thúy Nga, Lê Hùng Lân, Điều khiển robot bầy đàn tìm kiếm mồi và tránh vật cản sử dụng logic mờ, Tạp chí Khoa học Giao thông vận tải, 3 (2014) 15-20.
- [6]. Le Thi Thuy Nga, Nguyen Van Binh, Le Hung Lan, Stabilizing the Flexible Convergence of Swarm Robot by Fuzzy Attraction and Repulsion, Control Engineering and Applied Informatics, 24(2022) 58-66.
- [7]. Nga Le Thi Thuy, Thang Nguyen Trong, The Multitasking System of Swarm Robot based on Null-Space-Behavioral Control Combined with Fuzzy Logic, Micromachines, 8 (2017) 357. <https://doi.org/10.3390/mi8120357>
- [8]. K. Yamagishi, T. Suzuki, Cooperative Passing Based on Chaos Theory for Multiple Robot Swarms, Journal of Robotics and Mechatronics, 35 (2023). <https://doi.org/10.20965/jrm.2023.p0969>
- [9]. A. P. Singh, G. Kumar, G.Si. Dhillon, H.Taneja, Hybridization of chaos theory and dragonfly algorithm to maximize spatial area coverage of swarm robots, Evolutionary Intelligence, Vol.17, 2024, 1327-1340. <https://doi.org/10.1007/s12065-023-00823-5>.
- [10]. Y. Yaguchi, K. Tamagawa, A Waypoint Navigation Method with Collision Avoidance Using an Artificial Potential Method on Random Priority, Artificial Life and Robotics, 25 (2022) 278-285. <https://doi.org/10.1007/s10015-020-00583-w>
- [11]. B. Zhang, H. P. Gavin, Natural Deadlock Resolution for MultiAgent Multi-Swarm Navigation, 2021 60th IEEE Conf. on Decision and Control, (2021) 5958-5963. <https://doi.org/10.1109/CDC45484.2021.9683102>.
- [12]. L. Luo, X. Wang, J. Ma, Y.-S. Ong, GrpAvoid: Multigroup Collision-Avoidance Control and Optimization for UAV Swarm, IEEE Trans. on Cybernetics, 53 (2023) 1776-1789. <https://doi.org/10.1109/TCYB.2021.3132044>.