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Towards a Line Formation Algorithm to Reduce Congestion in Swarm Robotics

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***Abstract*—Inspired by natural phenomena such as fish schools and colonies, swarm robotics seeks to solve complex tasks through the cooperation of multiple simple robots. Despite significant advancements, the practical application of these systems faces challenges, particularly in scenarios where multiple robots share the same goal or have different goals within a common space. In such cases, the passage of a group of robots through a shared location can cause congestion. This work proposes an algorithm for line formation in swarm robotics, designed to reduce congestion in environments with spatial constraints. The methodology combines a flocking algorithm to maintain group cohesion with a line formation strategy, enabling robots to organize sequentially when traversing narrow areas. We conducted a series of simulations, varying the number of robots, to evaluate the proposed approach. The results demonstrate that the proposed approach significantly reduces congestion and the time required for a group of robots to pass through a common point. By combining flocking and line formation strategies, we present a promising solution for efficient swarm navigation in environments with spatial constraints, optimizing coordinated movement, and minimizing delays.**

***Index Terms*—Swarm Robotics, Congestion, Common Target, Line Formation, Cohesion Movement**

I. Introduction

Swarm robotics is a multi-agent system made up of numerous simple robots that work together in a coordinated way to accomplish tasks. These robots usually interact locally with their neighbors through communications or their exteroceptive sensors. Despite relying on simple rules and local information, the interaction between many robots generates emergent behavior that enables the group to solve complex tasks by leveraging system-level properties such as robustness, flexibility, and scalability [1]. The primary inspiration for swarms comes from groups of living beings, such as ant colonies, flocks of birds, and schools of fish [2].

Research in swarm robotics has made significant progress, with proof of concepts that demonstrate the potential of these systems and contribute to our understanding of how complex behaviors emerge in nature. However, applying these concepts to practical applications remains a major challenge [3].

In many practical applications, swarm robots must converge in the same area. In these situations, task delays can arise from conflicts in the agents' trajectories. In swarm robotics, decentralized collision avoidance algorithms have been proposed to address this challenge, offering both scalability and efficiency [4] [5]. Some studies propose controlling the parameters of an abstraction that involves the swarm, where each robot follows a potential field function to avoid colliding with others [6]. Another strategy is to control each robot using simple rules.

This work proposes an algorithm for line formation in swarm robotics, designed to reduce congestion in environments with spatial constraints. We introduce a line formation algorithm integrated into the potential field approach, combined with flocking [7]. This approach helps overcome the local minimum issue inherent in potential field methods and reduces the congestion when robots must reach the same area simultaneously. Given the significant number of robots in a swarm, line formation can cause conflicts in the robots' trajectories. To reduce these conflicts, the concept of rearranging regions was introduced. We illustrate these approaches through simulations and demonstrate the impact of using line formation and rearranging regions to reduce congestion.

This paper is organized as follows. In the next section, we present relevant related work. In Section III, we describe the fundamental concepts related to the combined approaches to guide the group toward the goals, while maintaining the group cohesion and avoiding obstacles. The simulations and results are presented in Section IV. Finally, Section V presents our conclusions and directions for future work.

II. Related Work

Potential Field Path Planning, as discussed in [8], has been widely applied in multi-agent systems due to its advantageous properties, such as scalability, reactiveness, and ease of integration with other methods. First introduced by Reynolds [7] to simulate large groups of agents acting collectively, flocking strategies rely on simple rules to guide agents. Potential fields and flocking approaches have been combined to produce

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cohesive movements that guide robots toward the goal while avoiding obstacles [9]–[12]. Many application domains have benefited from these strategies, including formation control [13] and herd behaviors [14].

In many applications, robots either share the same target or have different targets within a shared region. Such scenarios are commonly observed in waypoint navigation approaches, such as foraging as described by [15]. In such situations, robots collaborate to achieve a common objective and require efficient strategies to avoid collisions and congestion.

Collision avoidance is an important research topic in swarm robotics, as conflicts in the robots' trajectories can compromise the overall performance of the group. Marcolino [16] proposes dividing the region around the target, and depending on the region a robot reaches, it must wait for a while before proceeding to the target. This behavior is governed by a probabilistic finite state machine. As an extension of this work, the concepts of query former and vector fields were used in [17] to dictate the flow of robots around shared targets. Jiang *et al.* [18] apply geometric concepts to organize dispersed robots into a linear formation.

As described earlier, in this work we combine the concepts of flocking and line formation to provide a method for reducing congestion when a group shares a common target. Furthermore, we establish the concept of rearranging regions, enabling robots to reorganize themselves while moving toward a target.

III. METHODOLOGY

Our methodology is based on a combination of flocking behavior, potential field path planning, and line formation. We consider a swarm of fully actuated robots $\mathcal{S} = \{r_1, r_2, \ldots, r_n\}$ with kinematic model given by $\dot{\mathbf{q}}_i = \mathbf{v}_i$, where each robot i is represented by its pose $\mathbf{q}_i = [x_i \; y_i]^\intercal$. Using local sensors, each robot can sense its neighborhood and compute the resultant velocity $\dot{\mathbf{q}}_i = [\dot{x}_i \; \dot{y}_i]^\intercal$ that will guide it to the goal ($\mathbf{q}_{goal}$) while avoiding other agents and obstacles, and keeping it close to its group. We assume that an agent has access to the position and velocity of all other agents in its neighborhood or can infer these values based on its observations, and can exchange information with these agents. Finally, we consider that the robots start in an aggregated state and know the direction of a specific goal in the environment.

A. Potential field path planning

Potential field (PF) path planning methods treat a robot as a particle under the influence of an artificial potential field U. The potential U is a linear combination of attractive U_{att} and repulsive U_{rep} potential fields that only consider obstacles within a robot's neighborhood $\mathcal{N}$, such as:

$$U(\mathbf{q}_i) = U_{att}(\mathbf{q}_i) + \sum_{j \in \mathcal{N}_i} U_{rep,j}(\mathbf{q}_i). \tag{1}$$

In this work, the attractive artificial potential field was defined as follows:

$$U_{att}(\mathbf{q}_i) = \frac{k_{att}}{2} \rho_i(\mathbf{q}_{goal})^2, \tag{2}$$

in which k_{att} is a gain and $\rho_i(\mathbf{q}_{goal})$ is the Euclidean distance $\|\mathbf{q}_{goal} - \mathbf{q}_i\|$ between the robot i and the goal.

The repulsive artificial potential field considers all the obstacles near the robot, including the neighbor robots:

$$U_{rep,j}(\mathbf{q}_i) = \begin{cases} \frac{k_{rep}}{2} \left(\frac{1}{\rho_i(\mathbf{q}_j)} - \frac{1}{\delta_j} \right)^2, & \text{if } \rho_i(\mathbf{q}_j) < \delta_j \\ 0, & \text{if } \rho_i(\mathbf{q}_j) \geq \delta_j \end{cases} \tag{3}$$

where j is the j^{th} obstacle represented by $\mathbf{q}_j$, $\rho_i(\mathbf{q}_j)$ is the Euclidean distance between the robot i and this obstacle $\|\mathbf{q}_i - \mathbf{q}_j\|$, and δ_j is the maximum distance of influence from the obstacle j. A robot inside a robot's neighborhood is treated as an obstacle.

We assume that $U(\mathbf{q}_i)$ is a differentiable function, so $\mathbf{F}_{pf}(\mathbf{q}_i) = -\nabla U(\mathbf{q}_i)$ is the artificial force induced by the potential function at the actual configuration of a robot:

$$\mathbf{F}_{pf}(\mathbf{q}_i) = -\nabla U(\mathbf{q}_i) = -\nabla U_{att}(\mathbf{q}_i) - \sum_{j \in \mathcal{N}_i} \nabla U_{rep,j}(\mathbf{q}_i), \tag{4}$$

in which

$$\mathbf{F}_{att}(\mathbf{q}_i) = -\nabla U_{att}(\mathbf{q}_i) = k_{att}(\mathbf{q}_{goal} - \mathbf{q}_i)bl \tag{5}$$

and

$$\begin{aligned} \mathbf{F}_{rep,j}(\mathbf{q}_i) &= -\nabla U_{rep,j}(\mathbf{q}_i) \\ &= \begin{cases} k_{rep} \left(\frac{1}{\rho_i(\mathbf{q}_j)} - \frac{1}{\delta_j} \right) \frac{q_i - q_j}{\rho_i(\mathbf{q}_j)}, & \text{if } \rho_i(\mathbf{q}_j) < \delta_j \\ 0, & \text{if } \rho_i(\mathbf{q}_j) \geq \delta_j \end{cases} \end{aligned} \tag{6}$$

The resultant force $\mathbf{F}_{pf}(\mathbf{q}_i)$ is regarded as the promising direction that will guide the robot toward a goal while avoiding obstacles.

B. Flocking behavior

The flocking algorithm is a way to maintain group coherence during a motion. In [19], Reynolds proposed a flocking algorithm called *Boids*, inspired by the motion of some living beings, such as a flock of birds or a school of fish. This algorithm promotes emergent and complex behaviors by applying three simple rules: cohesion, alignment, and separation. These rules are applied locally, so each agent only considers another agents that are located inside its neighborhood, provided by a radius and an angle (gray area), as shown in Fig. 1.

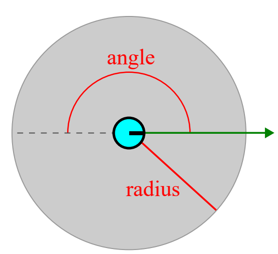


Fig. 1. Neighborhood of each robot represented by the gray area, defined by the angle and the radius.

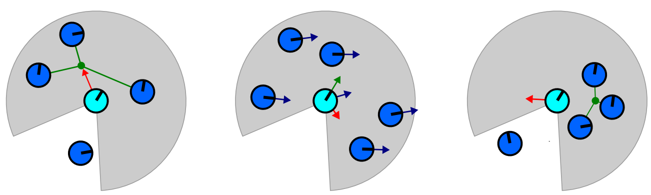
The cohesion rule directs an agent toward the center of mass of its neighbors, while the alignment rule adjusts its movement (direction and velocity) based on the neighbor's average. The separation rule prevents agents getting too close to others.

The cohesion force $\mathbf{F}_{coh}$ contributes to maintaining the group together and can be defined as follows:

$$\mathbf{F}_{coh}(\mathbf{q}_i) = k_{coh}\left(\frac{\sum_{j\in\mathcal{N}_i}\mathbf{q}_j}{|\mathcal{N}_i|} - \mathbf{q}_i\right), \tag{7}$$

where k_{coh} is the cohesion gain, $|\mathcal{N}_i|$ is the total number of robots within the neighborhood of the robot i, and $\mathbf{q}_j$ represents the configuration of the neighbor robot j.

The cohesion force contributes to maintaining the group together, and its behavior is illustrated in the Fig. 2(a).



(a) cohesion (b) alignment (c) separation

Fig. 2. Flocking rules of the cyan robot: (a) it is directed toward the center of mass of its neighbors; (b) it adjusts its movement based on the direction and velocity or its neighbors; (c) it steers to avoid crowding flockmates.

The alignment force $\mathbf{F}_{ali}$ adjusts the movement of a robot based on its neighbors' average direction and velocity, and is defined as follows:

$$\mathbf{F}_{ali}(\mathbf{q}_i) = k_{ali}\left(\frac{\sum_{j\in\mathcal{N}_i}\dot{\mathbf{q}}_j}{|\mathcal{N}_i|} - \dot{\mathbf{q}}_i\right), \tag{8}$$

in which k_{ali} is the alignment gain, $\dot{\mathbf{q}}_i$ and $\dot{\mathbf{q}}_j$ are the velocities of the robot and its neighbors, respectively, and $|\mathcal{N}_i|$ is the total number of robots inside the neighborhood of the robot i.

This force aims to adjust the robot's direction and velocity based on its neighbors (Fig. 2(b)).

The separation force $\mathbf{F}_{sep}$ steers the robot to avoid crowing flockmates, defined as:

$$\mathbf{F}_{sep}(\mathbf{q}_i) = k_{sep}\left(\mathbf{q}_i - \frac{\sum_{j\in\mathcal{M}_i}\mathbf{q}_j}{|\mathcal{M}_i|}\right), \tag{9}$$

where k_{sep} is the separation gain, $|\mathcal{M}_i|$ is the total number of robots within the separation neighborhood $\mathcal{M}_i$ of robot i, and $\mathbf{q}_i$ and $\mathbf{q}_j$ represent the configuration of a robot and its neighbor, respectively. This force prevents robots from getting too close to each other (Fig. 2(c)).

The separation neighborhood is similar to that shown in Fig. 1 but with a smaller radius.

Equation (10) defines the resultant flocking force, calculated by combining the three forces discussed earlier: cohesion, alignment, and separation.

$$\mathbf{F}_f(\mathbf{q}_i) = \mathbf{F}_{coh}(\mathbf{q}_i) + \mathbf{F}_{ali}(\mathbf{q}_i) + \mathbf{F}_{sep}(\mathbf{q}_i) \tag{10}$$

C. *Flocking and potential field path planning combination*

The line formation strategy presented in III-D considers a group of robots that act together. To provide a cohesive motion, the potential field approach (Section III-A) was combined with the flocking approach (Section III-B) as follows:

$$\mathbf{F}_c(\mathbf{q}_i) = \mathbf{F}_{pf}(\mathbf{q}_i) + \alpha\mathbf{F}_f(\mathbf{q}_i), \tag{11}$$

where $\alpha \in \{0, 1\}$ is defined based on the robot state (see Section III-D).

Taking into account the kinematic model described earlier, the forces will be assigned to velocities $\mathbf{v}_i = \mathbf{F}_c(\mathbf{q}_i)$, and the control law $\mathbf{u}_i$ will be:

$$\mathbf{u}_i = max(min(\|\mathbf{v}_i\|, v_{max}), v_{min})\frac{\mathbf{v}_i}{\|\mathbf{v}_i\|}, \tag{12}$$

in which v_{max} is used to limit the velocity of a robot, once $\mathbf{v}_i$ is proportional to $\|\mathbf{F}_{att}\|$. Moreover, a minimum velocity v_{min} was defined to maintain robots in motion even if they are too close to the goal: $v_{min} \leq \|\mathbf{u}_i\| \leq v_{max}$.

D. *Line formation strategy*

This strategy was proposed to overcome the target congestion observed when the group was only guided using the potential field approach combined with flocking, presented in Section III-C. The velocity of each robot is adjusted depending on its state, as defined in Fig. 3.

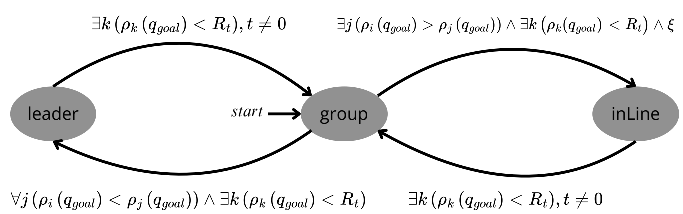


Fig. 3. Finite state machine defining the behavior of a robot i.

The initial state of every robot is *group*. When a robot is outside the congestion zone, its state remains *group* and it moves toward the goal while maintaining a cohesive motion — $\alpha = 1$ as defined in (11). Rearranging regions were defined as concentrical circles with a radius (R_t) centered on the target. These regions, numbered from 0 to n, were defined to allow the reconfiguration of the line of robots while they are moving in line. In this context, n denotes the number of rearranged regions. The larger region has radius R_0 and defines the edge of the congestion zone, while R_n is related to the target region that a robot must reach. The use of rearranging regions aims to enhance group performance and reduce congestion.

Whenever a robot goes beyond some rearranging region, its state can be changed, depending on its neighbors' states that share the same goal. When a robot passes through a rearranging region, its state can be changed as follows. If it is the robot closest to the target, its state changes to *leader* and it leads the line that guides the group toward the goal. The robot changes its states to *inLine* if it is not the closest one to the target, has a neighbor in states *leader* or *inLine*, and is the closest robot to some other robot in the line (which is represented by $\xi = true$). In this situation, the robot comes in line and follows its nearest neighbor — $\alpha = 0$ as defined in (11).

Taking into account the control law (12) derived from (11), the states' behavior illustrated in Fig. 3 can be summarized as:

- *group*: the combination of potential field and flocking guides the robot toward a goal with $\alpha = 1$;
- *inLine*: a robot follows some other robot whose state is *inLine* or *leader* using the potential field approach described earlier and using the parameter $\alpha = 0$;
- *leader*: a robot moves directly to the target with $\alpha = 0$.

Fig. 4 illustrates a line formation led by the red robot. The red line is used to highlight the robots that are in line. The edge of the congestion zone R_0 is emphasized by the orange semicircle. The blue color represents the state *group*, the green one represents *inLine*, and the red color represents the state *leader*. It is possible to note that the blue robot is not in line, therefore its state is *group*. This occurs because the blue robot is not the closest one to any other robot that is in line, and then ξ is $false$. As shown in the figure, the way the line is formatted can result in an unwanted situation because the robots in line can cause congestion to others in the group.

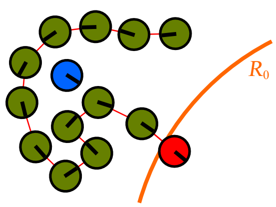


Fig. 4. Line formation process and the edge of the congestion zone R_0.

Rearranging regions were defined to provide a way to rearrange the line and reduce congestion. When passing a rearranging region, the robots alter their states to *group* and restart the line formation process. Thus, the robots reorganize themselves according to the state machine presented in Fig. 3, producing an adjusted line that is less congested.

IV. Experiments

To study the feasibility and performance of our proposed approach, we executed a sequence of simulations with the approaches described in Section III. Initially, we present the results, and some snapshots are used to illustrate the behavior of the group. We conducted three types of experiments to compare the time taken by the group to travel through the congestion zone. To do this, we recorded the time at which the first robot enters the congestion zone and the time when the last robot exits. Finally, we present a discussion related to this behavior and describe some aspects that impact the proposed approach.

We performed several experiments with swarms of different sizes. The group is placed according to a two-dimensional uniform distribution in a circular region outside the congestion zone. The initial state of all robots is set to *group*. Here we present instances of experiments with a swarm of 25 robots that aims to get the goal positioned in a narrow space. A video of an experiment is provided in this link: https://youtu.be/9_HcokomHbI.

Fig. 5 shows the success rate concerning the number of experiments that were successfully completed in both approaches. In the flocking and potential field path planning combination (Section III-C), the value of α was set to 1 in equation (11). An experiment is successful when all robots reach the goal. For the flocking and PF combination, the figure shows that as the number of robots increases, the rate of successful experiments decreases. This corroborates the local minima problem cited earlier.

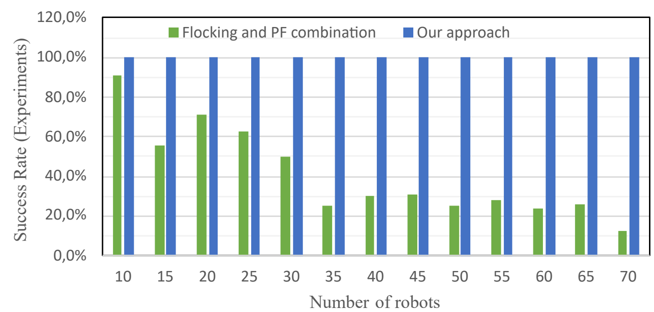


Fig. 5. Experiments comparing the success rate based on the number of experiments successfully completed.

Fig. 6 shows some snapshots of a particular instance of the experiments with potential field path planning and flocking combination (Section III-C). Through visual inspection, it is evident that the robots have difficulty passing through the narrow region (target). Moreover, the inherent problem of local minima can be observed in Fig. 6(d) where two robots were unable to achieve the goal.

The robot movement, guided using the approach discussed in Section III-D, is shown in Fig. 7. The same colors defined in Fig. 4 were used to represent the states: blue (*group*), green (*inLine*), and red (*leader*). Fig. 7(b) shows the first robot to enter the congestion zone, marked by the orange circle, which then becomes the leader. This situation initiates a chain of information exchanges, causing other robots to align with their nearest neighbors and transition their states to *inLine*. Consequently, the group can navigate the narrow region effortlessly. Using this strategy, the local minima and congestion issues presented in Fig. 6 were resolved, allowing all robots to reach the goal in 100% of the experiments.

Although these issues were resolved, some robots can not get in line unless they are the closest neighbor to another robot. Consequently, some robots might get lost and disperse from the group. Fig. 7(c) illustrates this kind of situation (blue robot). To overcome this issue, the concept of rearranging regions was proposed (see Section III-D). Many of these regions can be established, depending on the context. Fig. 9 presents the behavior of the group considering the rearranging region R_1, which is highlighted with a green circle in Fig. 9(c).

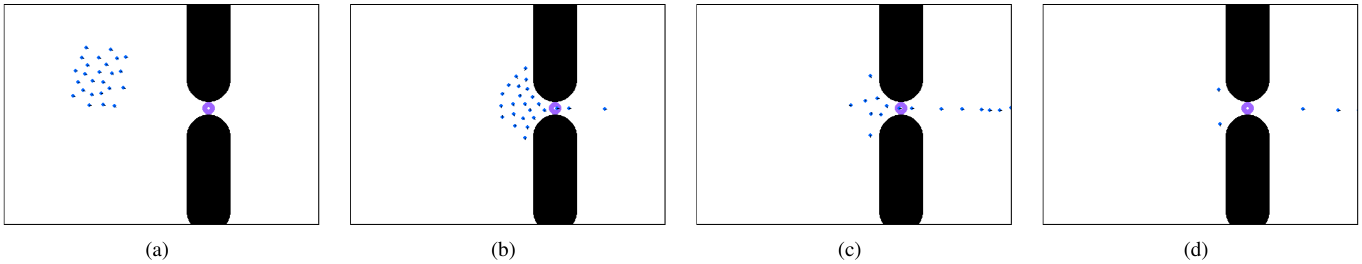


Fig. 6. Particular instance of the experiments with 25 robots that use potential field approach combined with flocking to guide them toward the goal (purple element). The goal was positioned in the narrow region to direct the group through that space. The initial configuration is presented in (a), while the last one is (d).

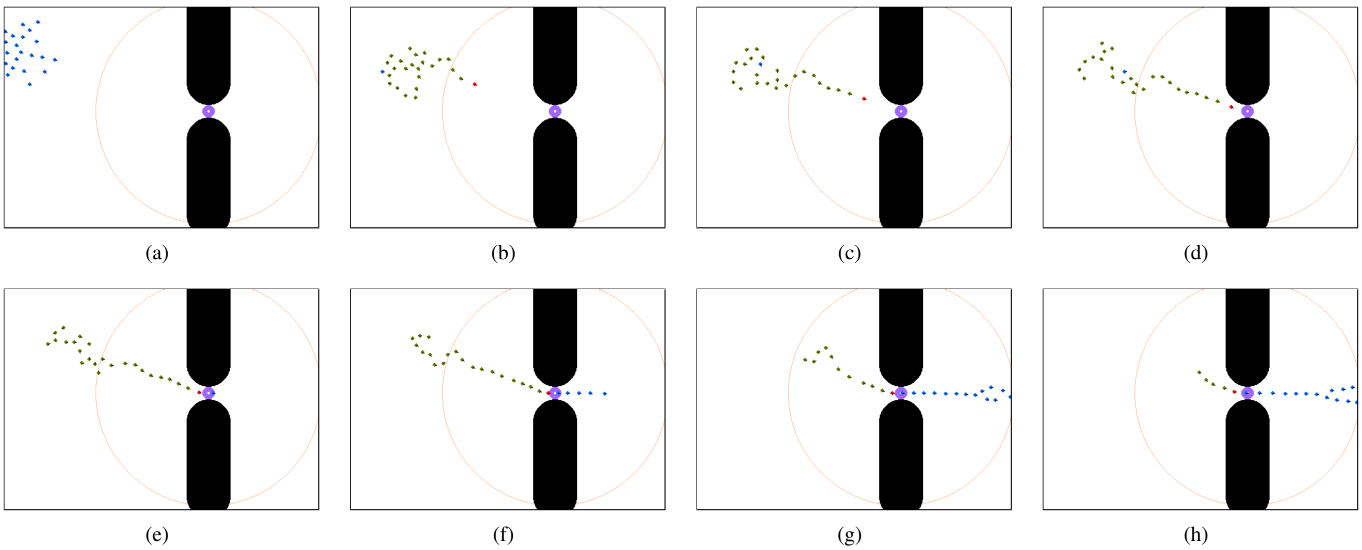


Fig. 7. Particular instance of the experiments with 25 robots using the proposed strategy of line formation without rearranging regions.

In the same figure, we can see a blue robot that fails to get in line (ξ is $false$). However, after the leader crosses the rearranging region R_1, the blue robot succeeds in getting in line.

Fig. 8 presents the execution time for a varying number of robots. As shown, our approach demonstrates better performance as the number of robots increases. Specifically, a *t-test* revealed that our approach performs well in all cases analyzed, with a confidence level of 95%. The bars represent two standard deviations from the mean of the results. The larger deviations arise from local minima that cause delays in the robots' progress.

Increasing the number of rearranging regions can improve the overall performance of the system because the group reorganizes itself many times. In this way, the situation illustrated in Fig. 4, where the line's configuration may interfere with the trajectories of some robots, tends to be mitigated. In future work, we plan to analyze whether this mitigation significantly reduces congestion in such scenarios.

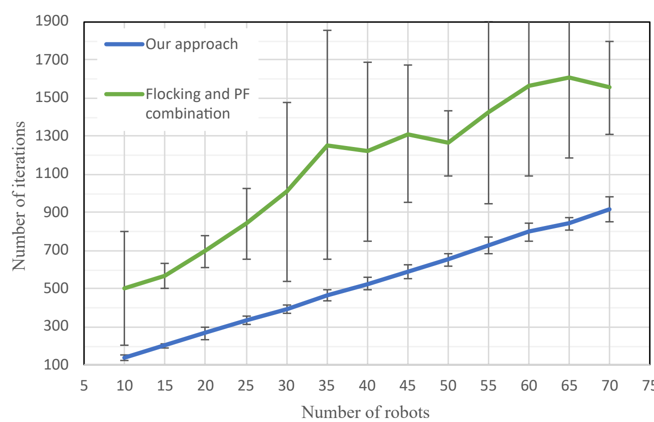


Fig. 8. Experiments comparing the time spent by the swarm with a confidence level of 95%.

V. Conclusion

This work presented an algorithm for line formation in swarm robotics designed to optimize the coordinated passage of multiple robots in spatially constrained environments, such as corridors and single-entry points. By combining a flocking algorithm with a potential field approach and a line formation strategy, the algorithm seeks to maintain group cohesion during the approach to the target and organize the robots into

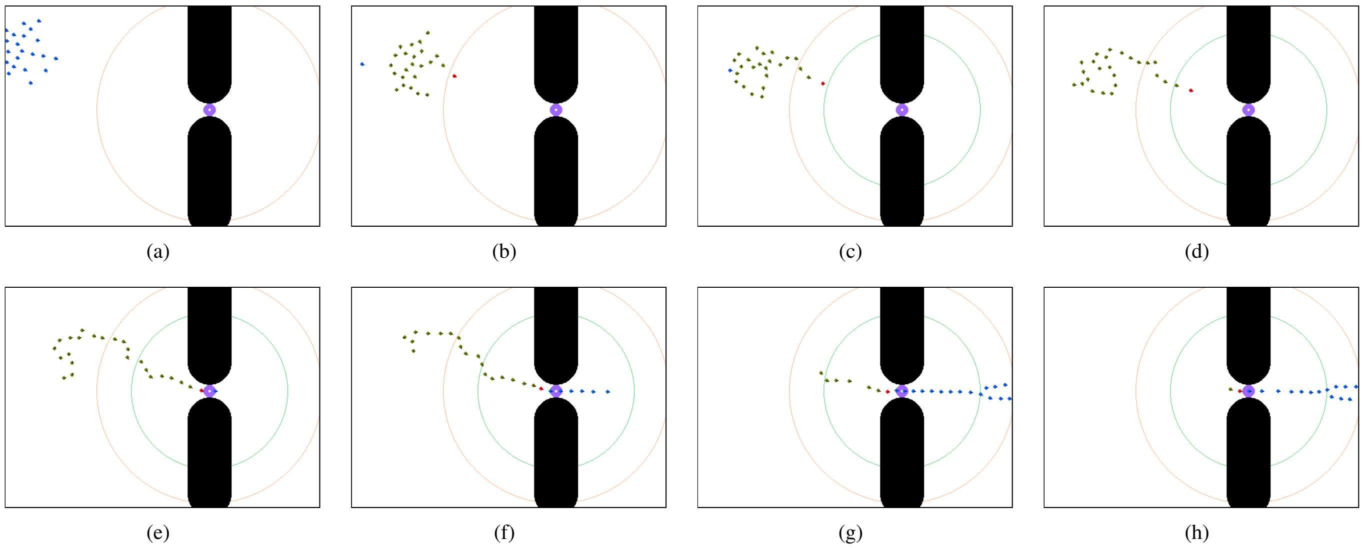


Fig. 9. Particular instance of the experiments with 25 robots using the proposed strategy of line formation with rearranging regions. The local minima and congestion issues were reduced, which allowed all robots to reach the goal.

a linear formation.

The experimental results demonstrate the effectiveness of the proposed approach in overcoming the limitations of traditional methods based solely on potential fields, which often struggle with local minima and congestion in narrow areas. The introduction of line formation allowed for a smoother and more efficient passage through narrow spaces. The use of rearranging regions (R_t) has proven to be effective in optimizing the line formation process. The comparative analysis of execution time presented in Fig. 8 demonstrates the superiority of our approach, especially as the swarm size increases. The *t-test* performed confirmed this superiority with a confidence level of 95% in all the cases analyzed.

Future work will explore the optimization of the quantity and positioning of rearranging regions, as well as the dynamic adaptation of line formation to more complex and dynamic environments. We aim to extend this approach to include the formation of multiple lines and the regrouping of robots. Finally, we are preparing experiments with real robots to better analyze the behavior of our approach in real scenarios.

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