Swarm Robots on a Mission: Optimizing Inspections with Fuzzy Logic and Particle Swarm Optimization

Nimra Sohail
Computer Engineering
Habib Univeristy
Karachi, Pakistan
ns06867@st.habib.edu.pk

Areeb Adnan Khan
Computer Engineering
Habib University
Karachi, Pakistan
ak06865@st.habib.edu.pk

Abdul Basit Memon
Electrical and Computer Engineering
Habib Univeristy
Karachi, Pakistan
basit.memon@sse.habib.edu.pk

***Abstract*—Swarm robotics is a captivating paradigm where a multitude of miniature robots collaborate to perform complex tasks with precision and speed. Coordination is crucial for seamless collaboration, and advanced algorithms play a pivotal role in optimizing swarm robot behavior. This survey highlights the transformative impact of swarm robots in various domains, such as disaster zone exploration and gas leak detection, and underscores the significance of coordination in achieving efficient and effective outcomes. This research survey explores the importance of advanced algorithms, Particle Swarm Optimization (PSO) and Fuzzy Logic Control (FLC), in coordinating swarm robots. The objective is to investigate their potential applications and shed light on their methodologies.The survey delves into the methodologies of PSO and FLC algorithms, which contribute to optimizing swarm robot behavior. PSO fine-tunes the behavior of individual robots by iteratively updating their positions based on individual best positions, while FLC establishes a rule-based framework that governs the overall swarm behavior. By combining PSO and FLC, swarm robots excel in tasks requiring precision, speed, and adaptability, adapting to dynamic environments efficiently. Through a comprehensive literature review, the survey examines the coordination mechanisms facilitated by these algorithms.It highlights their potential applications, showcases their effectiveness in optimizing swarm robot behavior, and discusses the challenges and areas for improvement. The expected results of this research survey include a deeper understanding of the capabilities and limitations of PSO and FLC algorithms in swarm robotics. The survey also summarizes key findings related to coordination strategies employed by swarm robots and offers recommendations for future research in this field. The findings highlight their potential to enhance coordination, precision, speed, and adaptability in various domains. By leveraging the collective intelligence of swarm robots, this research contributes to the ongoing advancements in swarm robotics and paves the way for transformative applications in real-world scenarios.**

***Index Terms*—Fuzzy logic, swarm robots, particle swarm optimization, coordination, decentralization.**

I. Introduction

Swarm robotics draws inspiration from the remarkable abilities of natural swarms, such as birds, bees, ants, and fish, which exhibit decentralized intelligence and collective behavior. This captivating phenomenon, known as Swarm Intelligence (SI), has garnered significant interest in the field. Swarm Intelligence offers a decentralized and flexible approach to problem-solving, making it well-suited for real-world optimization tasks like target search missions.

The decentralized control is a fundamental concept in swarm robotics, distributing control responsibilities among multiple agents within a swarm. This empowers individual robots to make autonomous decisions, fostering effective collaboration and adaptability to dynamic environments. By leveraging decentralized control, swarm robots can exhibit emergent behaviors, enhance robustness, flexibility, and scalability, and find applications in various domains such as search and rescue, environmental monitoring, and industrial automation.

In Swarm Intelligence, self-organized systems demonstrate decentralized collective behavior through various mechanisms. These mechanisms include stigmergy (indirect communication through environmental cues) [1], dispersion (spreading out) [2], aggregation (formation of cohesive groups) [3], and pattern formation (emergence of spatial structures) [4]. These self-organization principles contribute to the overall intelligence and efficiency of swarm robotic systems.

PSO and Fuzzy Logic are key components of Swarm Intelligence optimization. PSO optimizes movement patterns, while Fuzzy Logic aids navigation in complex environments. Combining them enhances swarm robots' performance in tasks like inspection and search, adapting efficiently to dynamic surroundings.

This paper explores PSO and Fuzzy Logic, highlighting their integration and real-world applications. It provides a comprehensive overview, including analysis of various parameters and variants of the algorithms, offering valuable insights for optimization in swarm robotics.

II. Idealizing the Searchspace

To facilitate the application of optimization strategies, it is essential to establish a suitable searchspace model. In the context of multi-robot cooperative operations, the method proposed in [5] is adopted due to its practical implementation and robustness against varying obstacle shapes. Fig 1 depicts the construction of a global coordinate system, denoted as o-xy. The x-axis aligns with the line connecting the start position (st) and the destination position (ta), while the y-axis is perpendicular to this line.

To delineate the searchspace, the line st-ta is discretized into ns + 1 sections by incorporating ns waypoints. The value of ns is predetermined based on user preferences or decisions. By employing a set of vertical lines l1, l2, l3, ..., lns+1, a candidate path for each robot is sought. This path, represented as p = [st, w1, w2, w3, ..., wns, ta], is explored along the aforementioned vertical lines. Such modeling of the searchspace allows for effective planning and navigation of robots, ensuring efficient coordination and achievement of desired objectives. The approach offers a practical and robust foundation for optimizing the performance of multi-robot systems in diverse environments.

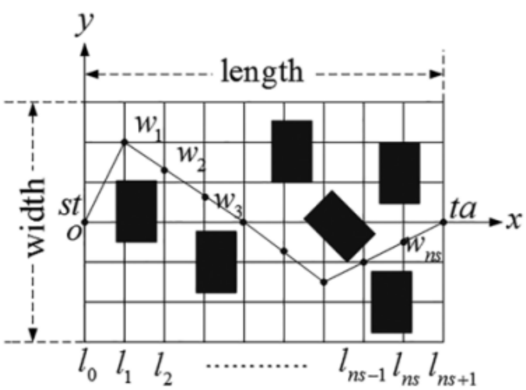

Fig. 1: Two-dimensional searchspace

III. Optimization Strategies

A. Particle Swarm Optimization

The traditional PSO algorithm, introduced by Kennedy and Eberhart [6], mimics the social behavior of bird flocks. Particles represent potential solutions and share positive information with neighboring particles, allowing the swarm to converge on locations with higher food concentrations.

In PSO, particles represent candidate solutions and traverse the search space to locate the optimal solution. They interact with neighboring particles, sharing information such as individual best solutions (local best) and the best solution within their neighborhood. The global best solution, obtained from the entire swarm, is updated at each step. With this collective information, particles learn from successful locations, adjust their trajectories, and evaluate their proximity to the optimal solution using the fitness function. Each particle maintains its own "personal best" solution, while the "global best" solution represents the best solution discovered by any particle in the swarm. Such a scenario is depicted in Figure 2 and Figure 3 as presented in [7].

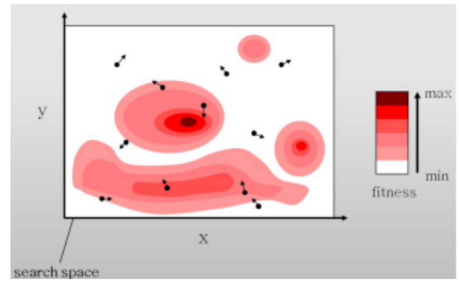

Fig. 2: Two-dimensional search space in PSO

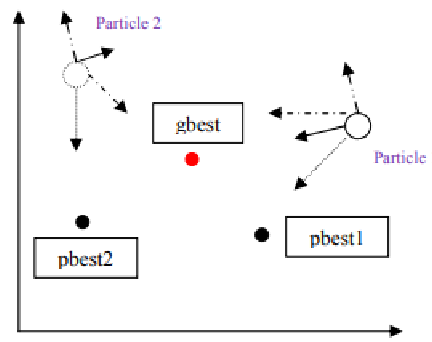

Fig. 3: Partcle motion in PSO

Fig 4 shows a general step-by-step flowchart algorithm of the bigger picture for PSO. Just like mentioned before fitness function is seen inputting values and then certain decisions are made.

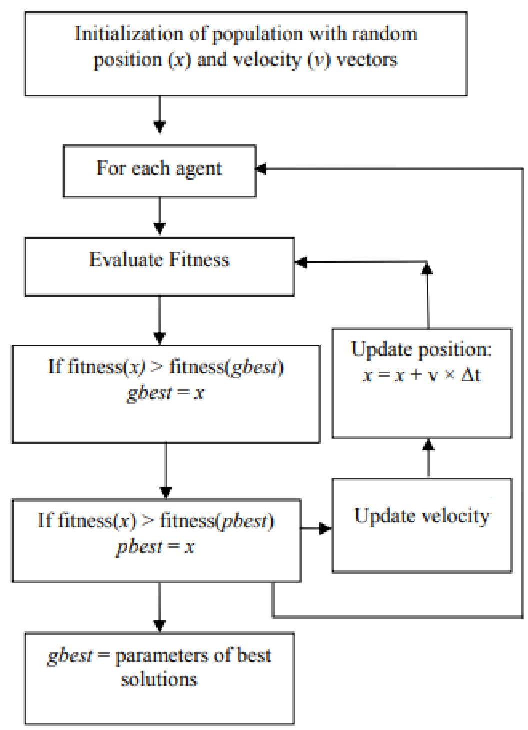

Fig. 4: PSO algorithm

Particles "i" in search space at iteration"t" updates its velocity and position using the following equations as given in [8] by:

$$v^i(t+1) = wv^i + c_1 r_1(p^i_{best} - x^i(t) + c_2 r_2(g_{best} - x^i(t))$$
$$x^i(t+1) = x^i(t) + v^i(t+1)$$

Here, w is the inertia coefficient, $v^i(t)$ is the velocity, $x^i(t)$ is the position, p^i_{best} is the personal best, g_{best} is the global best, rand is a random number, and c_1 and c_2 are learning factors. These equations guide the particle's movement towards the optimal solution by adjusting its velocity and position in the search space. The inertia weight w in PSO plays a crucial role in balancing global and local search abilities [9]. A large inertia weight promotes global search by allowing particles to explore a wider search space. In contrast, a small inertia weight facilitates local search by focusing particles on exploiting nearby regions. The choice of inertia weight depends on the optimization problem, with larger values favoring exploration and smaller values favoring exploitation. Selecting the optimal inertia weight is often determined through experimentation and fine-tuning.

An intriguing approach to examine the optimization technique involves visualizing contour plots. Figure 5 provides a visual representation of swarm particles within the contour plane. To generate the contour plot, the fitness function of the optimization problem is utilized. The swarm robots are initialized with random positions and velocities within the search space depicted by the contour plot. During each iteration, the fitness of each particle is assessed based on its position on the contour plot.

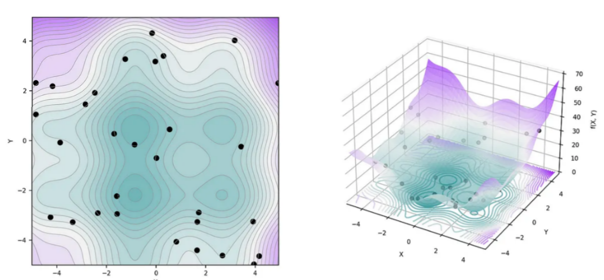

Fig. 5: PSO contour plot

B. Fuzzy Logic

Fuzzy Logic Theory is a decision-making technique that handles imprecise or uncertain information by translating linguistic values into specific values. The application of fuzzy logic presents an effective strategy for addressing uncertainty by employing straightforward linguistic logic rules, thereby avoiding the reliance on intricate mathematical models. This approach provides a practical and intuitive means of handling imprecise and ambiguous information, enabling more flexible and adaptable decision-making across diverse domains [10].

It is widely used in swarm robotics, specifically for obstacle avoidance and control systems involving multiple variables. The membership function in fuzzy logic control determines the degree of membership in a fuzzy set, such as the classification of an object as an obstacle based on input values like distance or size.

The fuzzifier transforms precise input values into fuzzy values using the membership function. These fuzzy values are used in the inference process, which applies predefined rules to determine the robot's actions based on input conditions. The defuzzifier then converts the fuzzy output values back into precise values for controlling the robot's movement. This is depicted in Figure 6 as presented in [11]. Fuzzy logic in swarm robotics analyzes inputs such as robot distances, obstacles, and sensor readings to coordinate and determine appropriate responses.

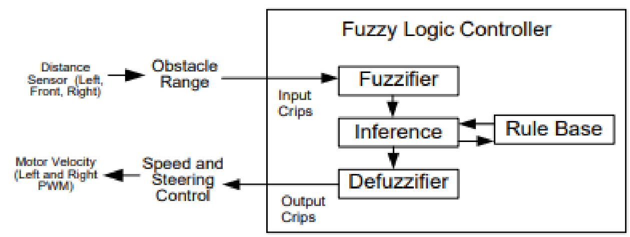

Fig. 6: Fuzzy Logic Controller

Fuzzy logic is employed to incorporate input from sensors into membership functions (MFs), enabling the generation of rules that govern the robot's response to its surroundings [12]. These rules guide the robot's interactions with the environment, allowing it to adapt its behavior towards achieving specific goals. By leveraging fuzzy logic, the robot can effectively navigate and respond to its environment, exhibiting adaptive and context-aware behavior.

C. Synergy between PSO and Fuzzy logic

This section delves into two techniques that contribute to the coordination and execution of inspection tasks by swarm robots: fuzzy PSO and its hybrid algorithm. By integrating fuzzy logic and particle swarm optimization, fuzzy PSO enables swarm robots to handle imprecise inputs, including obstacles and other robots. The hybrid nature of fuzzy PSO provides a robust solution for swarm robots engaged in inspection tasks, allowing them to adapt and respond to dynamic circumstances effectively. Through the utilization of fuzzy rules and PSO-based movement optimization, swarm robots can make intelligent decisions and navigate complex environments with efficiency. This integration not only enhances coordination and cooperation among swarm robots but also facilitates the exploration and inspection process.

During the iterative process of algorithm in Figure 7, it is observed that there are variations in speed. Swarm robots equipped with sensors for target detection can adjust their speed based on the fuzzy-PSO technique to locate specific targets. This adaptive speed control mechanism enables swarm robots to optimize their inspection performance by dynamically responding to the environment.

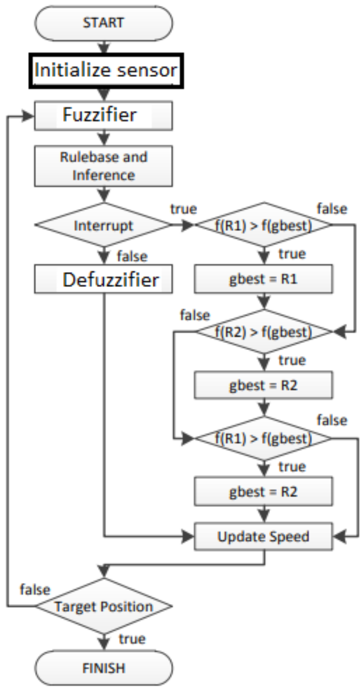

Fig. 7: Fuzzy-PSO algorithm [13]

Another paper in [14] links PSO with FLC and emphasizes the benfit of using Fuzzy-PSO.In swarm robotics, selecting appropriate fuzzy parameters is vital for defining individual robot behavior and achieving coordinated collective behavior. The traditional manual tuning process for these parameters can be time-consuming. However, by integrating PSO, swarm robots can automatically optimize fuzzy parameters for effective coordination and decision-making. PSO explores the parameter space and converges towards optimal parameter values. This automated approach improves performance, adaptability, and saves time and resources. By combining fuzzy control with PSO, swarm robots can handle uncertainty, make decisions based on simple linguistic rules, and seamlessly adapt to dynamic environments.

In line with existing research, the combination of fuzzy logic controller (FLC) and PSO has attracted considerable attention [15]. The integration of parameter adjustment methods, such as dynamic tuning and fuzzy logic, has played a vital role in enhancing the effectiveness of PSO for target search problems. Notably, a study in [16] focused on employing dynamic parameter adjustment to enhance the completion of target searching tasks performed by swarm robots. Similarly, another research endeavor [17] proposed a PSO strategy that incorporated a fuzzy logic controller for landmine detection and firefighting using swarm robots. These investigations effectively utilized parameter adjustment techniques to optimize the performance of the PSO algorithm.

By dynamically adapting the parameters, the algorithm achieves improved efficiency, enabling swarm robots to carry out target search tasks with greater effectiveness. The integration of fuzzy control and PSO enhances self-organization, cooperation, and objective achievement in swarm robotics.

IV. Key Findings

In the study conducted by researchers in [13], the Fuzzy-PSO algorithm was employed to enable three swarm robots to navigate a simple environment with minimal obstacles towards a specified destination. The algorithm leveraged the combined power of fuzzy logic and particle swarm optimization to optimize the robots' movement patterns and facilitate efficient obstacle avoidance.

This study in [18] explores the combined use of Fuzzy Logic and Particle Swarm Optimization (PSO) for precise control of a robotic arm actuator, specifically a DC linear servo engine. The simulation results in Table I demonstrate significant improvements compared to previous techniques, achieving faster results within a single cycle. Advanced control-equipped industrial robots find applications in diverse sectors like materials handling, painting, and welding, among others.

TABLE I: Comparison of Robot Characteristics with Different Control Methods

Controller	Robot Steady-State Error
Conventional controller	0.064
Fuzzy controller	0.036
Fuzzy-PSO controller	0.007

In another investigation [19], the Fuzzy-PSO algorithm was applied to trace gas leakage using swarm robots. The study assessed the algorithm's effectiveness by analyzing various parameters. Table II illustrates the results of the parameter analysis, demonstrating how the Fuzzy-PSO algorithm enhances coordination and enables faster task completion among the seven participating robots.

TABLE II: Fuzzy-PSO vs no optimization algorithm parameter analysis

Parameter	Fuzzy-PSO	No Fuzzy-PSO
Elapsed time(steps)	207.6	219.3
Speed	stable	unstable
Steer of motor	stable	unstable

In addition to the previous investigation, another study [20] highlights the significant advantage of employing the combination of Fuzzy-PSO for target search. The lack of coordination among the robots, as depicted in Figure 9, results in individual running behavior, where each robot avoids obstacles and other robots independently. However, in Figure 8, the robots demonstrate coordinated movement. They are able to follow the robot with the closest position to the center of the gas leakage, while effectively avoiding obstacles and other robots. This coordinated behavior is evident in the smooth trajectory of the robot's path when navigating around obstacles and interacting with other robots.

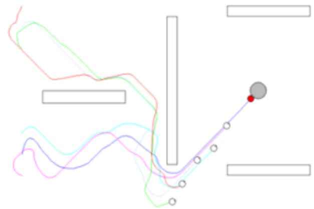

Fig. 8: Target search with Fuzzy-PSO

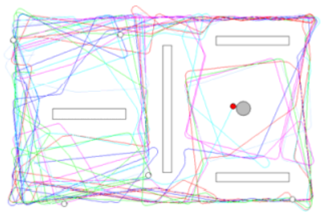

Fig. 9: Target search without Fuzzy-PSO

In a comparative study in [21], the effectiveness of the Fuzzy-PSO algorithm was evaluated alongside Fuzzy-Kohonen Network (FKN) and FKN-PSO. Performance metrics of time to target detection and time to reach the target were considered. The results indicated that Fuzzy-PSO outperformed FKN in both metrics, but had slightly lower performance compared to FKN-PSO as shown in Table III.

TABLE III: Performance of FKN, Fuzzy-PSO, and FKN-PSO

Parameter	FKN	Fuzzy-PSO	FKN-PSO
Time to target detection(sec)	17	10	2
Time to reach target(sec)	43	30	14

PSO has demonstrated its effectiveness in addressing a wide range of optimization problems. However, like other stochastic search techniques, it faces a significant challenge known as premature convergence [22]. Premature convergence occurs when the algorithm settles on a suboptimal solution too early, without fully exploring the search space or finding the global optimum. This issue is particularly prominent in multimodal optimization problems with complex landscapes. The consequences of premature convergence are detrimental to the performance of PSO. It limits the algorithm's ability to find the optimal solution or discover diverse solutions in scenarios with multiple peaks or modes. The swarm particles tend to converge towards a local optima, neglecting other potentially better solutions.

To overcome premature convergence, researchers have proposed various strategies and modifications. These approaches aim to enhance the exploration capability of PSO, preventing it from getting trapped in suboptimal solutions. Such as in [23], the authors have conducted a remarkable comparison between Adaptive PSO (APSO) and Fuzzy Logic. They have utilized an advanced and more parameterized version of PSO called APSO. The results of this comparison, including performance metrics, are presented in Table IV. The findings shed light on the effectiveness of APSO in minimizing the trajectory length.

TABLE IV: Comparision in trajectory length(m) for mobile robot to search for target

Parameter	Fuzzy Logic	APSO
Trajectory length(m)	3.43	3.27

In a separate study [24], a simulation involving 100 robots with independent obstacle avoidance modules was conducted. The robots successfully achieved the target under the guidance of mechanical PSO, as depicted in Figures 10 and 11.

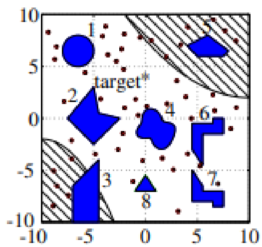

Fig. 10: Initial Status

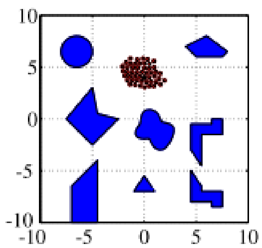

Fig. 11: Final status

The PSO-based model, as described in [25], offers different variants for robotic swarm searching tasks. One such variant is Robotic PSO (RPSO), which enhances the standard PSO algorithm by including elements specifically designed for obstacle avoidance. Another variant, Modified Local PSO (MLPSO), prioritizes local search capabilities by enabling particles to explore their local neighborhoods and exchange information with neighboring particles. These variants contribute to improved search performance in swarm robotics. Additionally, Table V provides a valuable comparison, highlighting how increasing the number of robots in a search space facilitates the discovery of a larger number of targets.

TABLE V: Comparision between RPSO and MLPSO based on no.of robots and targets to search

No of Robots	Targets Achieved	
	MLPSO	RPSO
10	3	1
25	7	2
35	8	4
50	9	5

The aforementioned findings highlight the high standards achieved by PSO and FLC. When working together, PSO and FLC demonstrate a strong synergy, enabling swarm robots to efficiently carry out target searches. However, it should be noted that the basic version of PSO may not yield satisfactory results on its own. Therefore, the utilization of advanced variants of PSO becomes essential. Furthermore, optimization strategies play a crucial role in accelerating the search process, while a larger number of swarm robots can significantly expand the scope of search targets.

V. Conclusion

The research in swarm robotics has highlighted the effectiveness of Swarm Intelligence (SI) optimization strategies.

The integration of Particle Swarm Optimization (PSO) has enabled swarm robots to optimize their movements and navigate complex environments by leveraging iterative position updates based on best solutions. Additionally, the incorporation of Fuzzy Logic has enhanced their ability to handle uncertain information, enabling flexible decision-making and efficient obstacle avoidance. The combination of PSO and Fuzzy Logic has demonstrated improved performance in target search missions, obstacle avoidance, and swarm coordination. Overall, the integration of PSO and Fuzzy Logic in swarm robotics offers a powerful approach to problem-solving. It allows swarm robots to adapt to dynamic environments, make intelligent decisions, and successfully accomplish complex tasks. Future research can focus on further refining and expanding these optimization strategies to address more intricate scenarios and advance the capabilities of swarm robots in various domains.

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