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# Developing a Navigation System in a Dynamic Environment Based on Swarm Intelligence

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**Abstract:** Autonomous systems are having a lot of difficulty in navigating in dynamic situations as the placements of obstacles are always changing, conditions are unpredictable and quick decisions are required. Traditional methods of navigation are often limited in their flexibility and effectiveness in highly dynamic situations. Swarm intelligence is a possible computer paradigm inspired by the collective behavior of biological systems such as ants, bees, birds and wolves. Because of their distributed decision making, adaptability, robustness, and optimization features, these algorithms are well suited for hard navigation problems. Recent advances in swarm based algorithms like Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Gray Wolf Optimizer (GWO) and Artificial Bee Colony (ABC) have shown remarkable performance in the applications of obstacle avoidance and path planning. This study investigates the use of swarm intelligence techniques in designing an intelligent navigation system that can work in dynamic environments. In the paper we present the recent progress, describe the algorithmic frameworks and mathematical models and discuss the difficulties in real time navigation.

**Keywords:** Swarm Intelligence, Dynamic Environment, Path Planning, Obstacle Avoidance, Particle Swarm Optimization, Autonomous Navigation, Multi-Agent Systems.

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## 1. Introduction

The rapid development of autonomous systems, intelligent robotics and unmanned vehicles, increases the need for advanced navigation methods that can function in challenging and ever-changing situations. Navigation is one of the key components of autonomous systems as it enables an intelligent agent, robot or autonomous vehicle to choose an adequate route from a known starting point to a required destination whilst satisfying operational and environmental constraints. Traditional navigation and path-planning systems have performed very well in structured and predictable situations, but when the operational environment becomes dynamic, uncertain or only partially observable, their performance can degrade dramatically. Additional challenges include moving obstacles, changing environmental conditions, unpredictable behavior of the agent, and differences in available paths, all of which require highly adaptive navigation systems with decision-making capabilities.

Dynamic environments are inherently different from static ones as the best navigation path may continuously change because of obstacles and other autonomous agents. A route that is effective and safe at one time might become inaccessible or dangerous a short time later. Therefore navigation systems in dynamic environments, need to find not only collision free paths, but also need to continually check changes in the environment, reconsider their knowledge about the environment and produce new alternatives when the current path is no longer suitable. These requirements have motivated researchers to explore computational and intelligent optimization techniques that can make adaptable, flexible, and near-optimal navigation decisions in real time.

In this context a promising computational paradigm for the design of intelligent navigation systems is the Swarm Intelligence (SI). Swarm intelligence is inspired by the collective behavior of biological organisms such as ants, bees, birds, fish and other social species that are able to achieve complex goals through relatively simple individual behaviors and decentralized interactions. The basic idea of swarm intelligence is that intelligent global behavior can emerge from local interaction of several simple agents without a centralized controller. Swarm based techniques are particularly attractive for autonomous navigation because the system must react fast and efficient to changes in the environment.

Several swarm intelligence algorithms have been used for studies of path-planning and navigation problems such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) and other bio-inspired optimization methods. These algorithms are capable of exploring large and complex solution spaces and optimizing the navigation paths according to several criteria such as computational cost, path length, travel time, energy consumption, safety and obstacle avoidance. However, there are some difficulties for the direct implementation of the swarm intelligence in dynamic contexts. Standard optimization

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methods can yield solutions that become obsolete with changing environments, converge slowly, or get stuck in local optima. Therefore, the swarm intelligence algorithms should be adjusted based on the characteristics of dynamic environments to create an efficient navigation system.
Hence, the design of a swarm intelligence based navigation system encompasses the integration of environmental sensing, path planning, obstacle detection, optimization and real time decision making in a unified framework. Such a system must be able to sense changes in the environment, evaluate the safety and quality of alternative routes, and adjust its navigation strategy dynamically to take into account newly identified circumstances. The system effectiveness can be evaluated using a variety of performance indicators, such as the navigation success rate, path length, computation time, collision avoidance capability, convergence speed, adaptability to environmental changes, and the overall system efficiency.
This research is important since autonomous navigation technologies are increasingly used in various applications including mobile robots, autonomous vehicles, unmanned aerial vehicles, intelligent transportation systems, warehouse automation, search and rescue operations, and military and industrial applications. In many of these applications the navigation system must operate in environments where barriers and other agents can move erratically. Failure to react properly on such changes may cause ineffective movement, collision, more energy consumption or complete failure to reach the destination. Hence, improving the flexibility and reliability of autonomous navigation remains a key research challenge.

## 2. Background

Swarm intelligence is a subfield of artificial intelligence based on the collective behavior of natural systems such as ant colonies, flocks of birds, swarms of bees and packs of wolves.[1] Swarm-based techniques outperform centralized systems in terms of efficiency in achieving complex tasks by decentralized interactions among simple agents.[2]
The idea has received much attention due to its ability to solve nonlinear and uncertain optimization problems.[3] Swarm intelligence techniques allow autonomous agents in navigation applications to minimize the trip distance, avoid collisions and continuously update their paths in response to changes in the environment.[4]

### 2.1. Swarm Intelligence Concepts

Swarm intelligence is a collection of computer techniques inspired by the collective behavior of biological groups.[5] Unlike traditional optimization techniques that are based on centralized control, swarm intelligence algorithms work on the principle of decentralized interaction of several agents to solve difficult optimization problems.[6] These algorithms are inspired by

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natural phenomena such as bee communication, ant foraging, bird flocking and wolf hunting strategies.[7]

Self-organization is an important characteristic of swarm intelligence. The behavior of individual agents is governed by simple local rules, with no need for a central supervisor. The whole swarm shows intelligent behavior and reaches optimal or near-optimal solutions by cooperation and exchange of information.[8]

### 2.2. Mathematical Modeling of Dynamic Environments

Dynamic environments are characterized by continuous variations in obstacle positions and environmental conditions.[9] The navigation problem is formulated as an optimization process where the objective function minimizes path cost:[10]

$$F(x) = \alpha \cdot L + \beta \cdot E + \gamma \cdot C \quad \text{... (Eq. 1)}$$

**where:** $L$ = path length; $E$ = energy consumption; $C$ = collision risk; $\alpha, \beta, \gamma$ = weighting coefficients.

The position of moving obstacles at time t is represented as:[11]

$$O_i(t) = (x_i(t), y_i(t)) \quad \text{... (Eq. 2)}$$

The position of the autonomous robot is defined by:

$$R(t) = (x(t), y(t)) \quad \text{... (Eq. 3)}$$

Collision avoidance requires maintaining a minimum safe distance:

$$D(R, O_i) \geq D_safe \quad \text{... (Eq. 4)}$$

where D_safe is the predefined safety threshold. These models enable navigation algorithms to adapt trajectories while preserving safety and optimality.

### 2.3. Particle Swarm Optimization (PSO)

Particle Swarm Optimization, originally proposed by Kennedy and Eberhart, simulates the social behavior of bird flocks and fish schools. [12] Each particle represents a candidate solution moving through the search space according to its own experience and neighboring particles.

The velocity update equation is: [13]

$$V_i(t+1) = w \cdot V_i(t) + c_1 \cdot r_1 \cdot (Pbest_i - X_i(t)) + c_2 \cdot r_2 \cdot (Gbest - X_i(t)) \quad \text{... (Eq. 5)}$$

**where:** $V_i$ = particle velocity; $X_i$ = particle position; $Pbest_i$ = personal best; $Gbest$ = global best; $w$ = inertia weight; $c_1, c_2$ = acceleration constants.

The particle position is updated as:

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad \text{... (Eq. 6)}$$

PSO exhibits fast convergence and low computational complexity in dynamic navigation. However, premature convergence and local optima remain major limitations.

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### 2.4. Ant Colony Optimization (ACO)

Ant Colony Optimization is inspired by the foraging behavior of real ants that communicate through pheromone trails. The probability of selecting a path is: [14]

$$P_ij = (\tau_i\square\text{^}\alpha \cdot \eta_i\square\text{^}\beta) / \Sigma(\tau_i\square\text{^}\alpha \cdot \eta_i\square\text{^}\beta) \quad \text{... (Eq. 7)}$$

**where:** $\tau_i\square$ = pheromone intensity; $\eta_i\square$ = heuristic information; $\alpha$, $\beta$ = influence control parameters.

Pheromone updating follows: [15]

$$\tau_i\square(t+1) = (1 - \rho)\cdot\tau_i\square(t) + \Delta\tau_i\square \quad \text{... (Eq. 8)}$$

where ρ is the evaporation coefficient. ACO provides robustness against dynamic changes, though convergence speed may decrease in highly complex environments.

### 2.5. Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer mimics the leadership hierarchy and hunting mechanisms of grey wolves. Wolves are categorized into alpha (α), beta (β), delta (δ), and omega (ω). Alpha represents the best solution; others update their positions accordingly. [16]

The encircling prey formulation is: [17]

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \quad \text{... (Eq. 9)}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad \text{... (Eq. 10)}$$

**where:** $\vec{X}_p$ = prey position; $\vec{A}$, $\vec{C}$ = coefficient vectors controlling exploration and exploitation.

GWO provides efficient global search capability and strong performance against local optima, making it highly effective in dynamic environments.

### 2.6. Artificial Bee Colony (ABC)

Artificial Bee Colony optimization imitates the foraging behavior of honey bees. The colony consists of employed bees, onlooker bees, and scout bees. The position update mechanism is: [18]

$$V_i\square = X_i\square + \varphi_i\square\cdot(X_i\square - X\square\square) \quad \text{... (Eq. 11)}$$

**where:** $X_i\square$ = current solution; $X\square\square$ = neighboring solution; $\varphi_i\square \in [-1, 1]$ is a random number.

ABC algorithms maintain diversity among candidate solutions, making them suitable for dynamic navigation with unpredictable changes.

### 2.7. Comparative Analysis of Swarm Intelligence Algorithms

Table 2 provides a comprehensive comparison of the four main algorithms across key performance metrics relevant to dynamic navigation systems.[19]

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Table 2: Algorithm Comparison Matrix

| Criterion | PSO | ACO | GWO | ABC |
|---|---|---|---|---|
| **Convergence Speed** | Very Fast | Moderate | Fast | Moderate |
| **Accuracy** | Moderate | High | High | Moderate-High |
| **Execution Time** | Low | High | Moderate | Moderate |
| **Energy Consumption** | Low | Moderate | Low-Moderate | Moderate |
| **Obstacle Avoidance** | Good | Excellent | Excellent | Good |
| **Local Optima Risk** | Medium (prone) | Low | Low | Low |
| **Scalability** | High | Moderate | High | Moderate |
| **Key Advantage** | Simple, fast | Distributed, robust | Balanced explore/exploit | High diversity |
| **Key Limitation** | Premature conv. | Slow in complex envs. | Needs tuning | Slow convergence |

Table 3: Algorithm Applications by Domain

| Application Domain | PSO | ACO | GWO | ABC |
|---|---|---|---|---|
| **Mobile Robots** | Path planning | Shortest-path nav. | Collision-free nav. | Adaptive nav. |
| **UAV / Drones** | Swarm formation | Route optimization | 3D path planning | Task allocation |
| **Autonomous Vehicles** | Dynamic routing | Traffic flow opt. | Lane planning | Fuel optimization |
| **Search & Rescue** | Multi-robot search | Area coverage | Victim localization | Task distribution |
| **Agriculture** | Crop field planning | Row path planning | Terrain navigation | Precision farming |
| **Space Exploration** | Rover path plan. | Resource mapping | Planetary navigation | Multi-rover coop. |
| **Military** | Drone swarm tactics | Route recon. | Stealth navigation | Resource allocation |

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### 2.8. Proposed Navigation System Architecture

The proposed navigation framework combines swarm intelligence algorithms with real-time environmental sensing.[20]

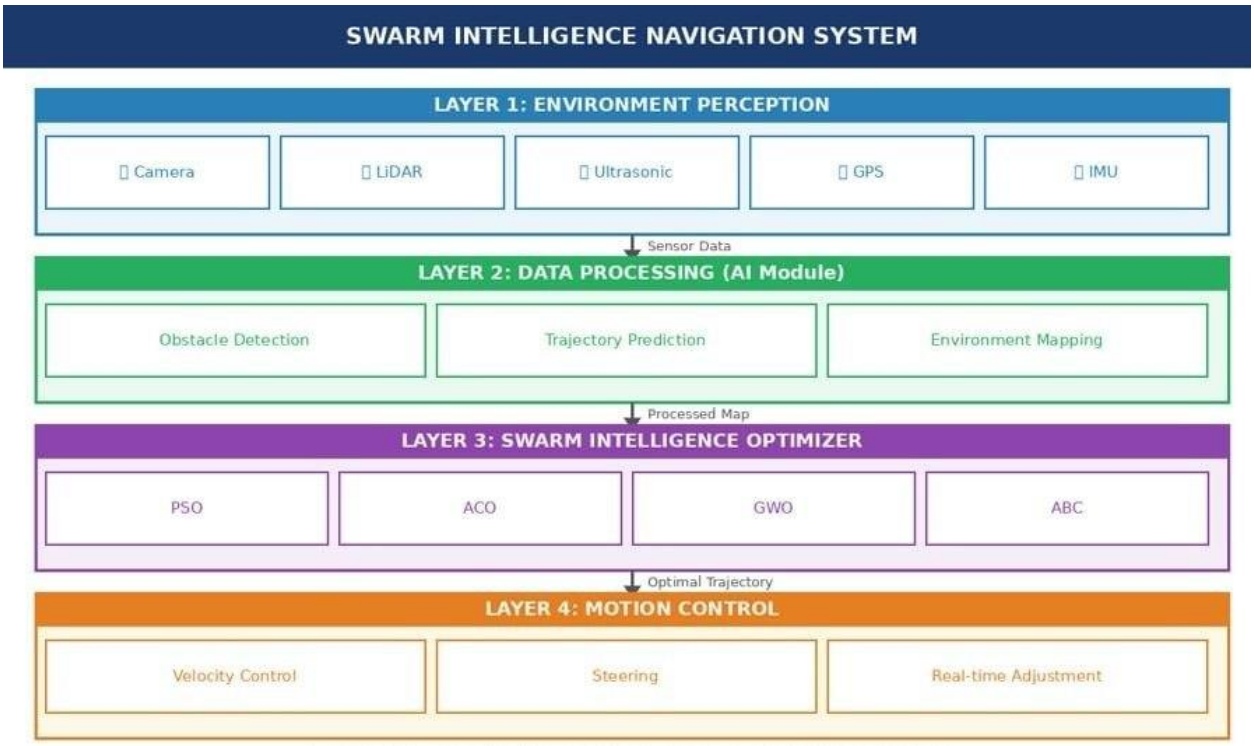



Figure1. Four-layer architecture of the proposed swarm intelligence-based navigation system

The system is composed of four primary layers:[21]

- Environment Perception Layer: Real-time environmental data is collected by cameras, LiDAR, ultrasonic sensors, GPS and IMU.
- Data Processing Layer: Environmental maps construction, route prediction, obstacle detection by standard artificial intelligence systems.
- Swarm Intelligence Layer : PSO, ACO, GWO and ABC produces optimal collision free trajectories.
- Motion Control Layer: The robot then follows the chosen path in real-time.

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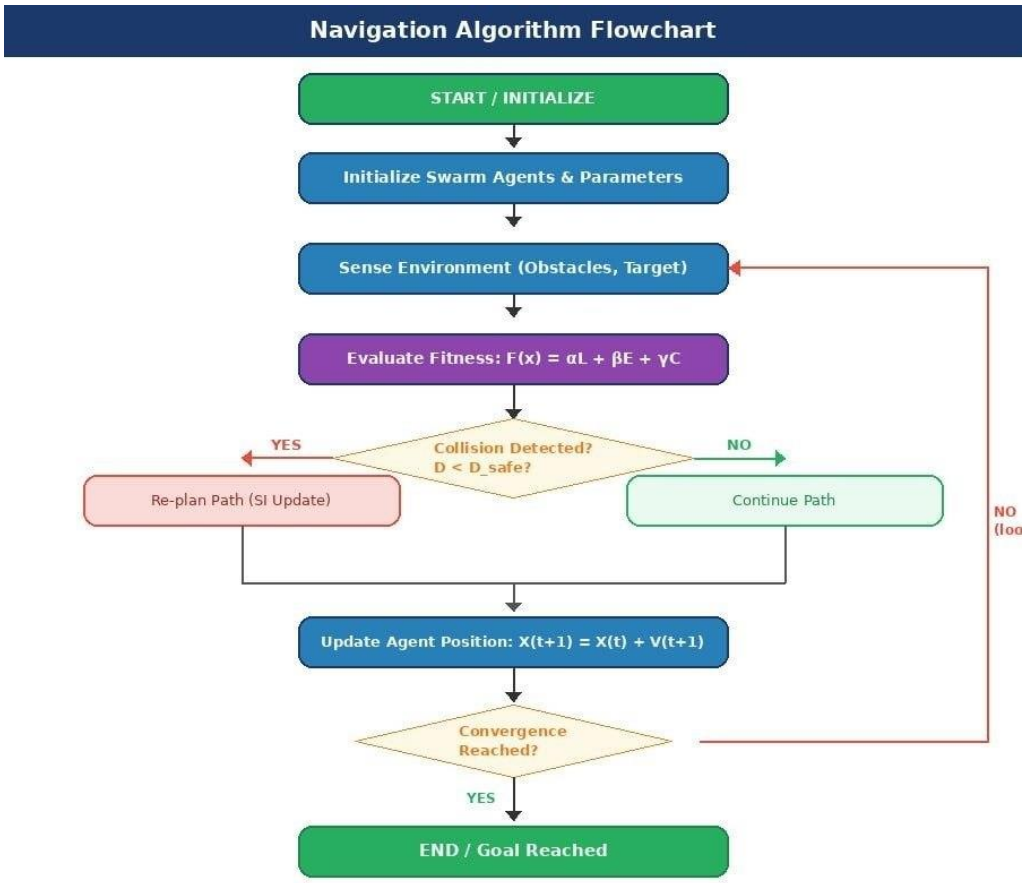



Figure.2 Flowchart of the proposed swarm intelligence-based navigation algorithm

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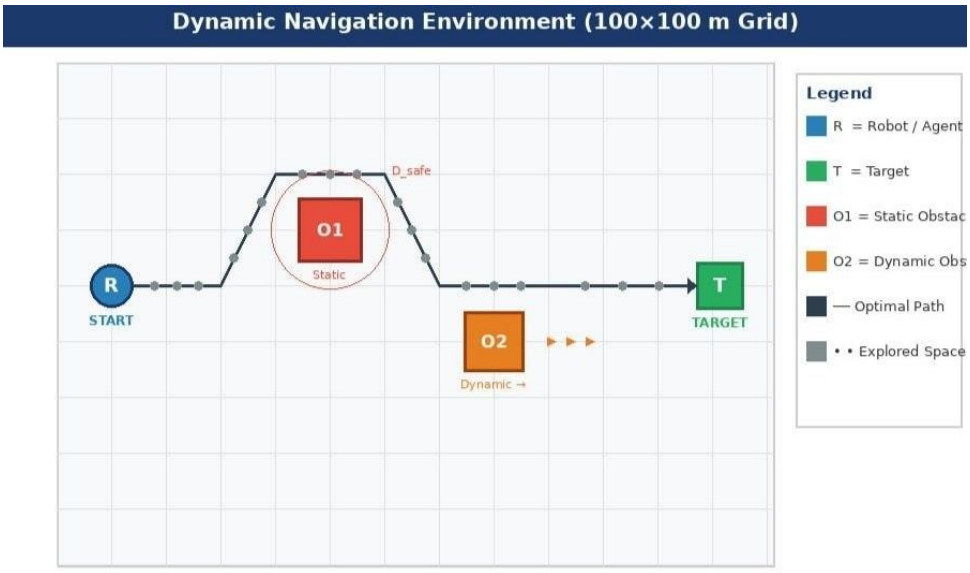



Figure 3. Dynamic navigation environment.

### 2.9. Obstacle Avoidance Mechanism

Obstacle avoidance is a fundamental requirement for autonomous navigation. The Euclidean distance between the robot and obstacles is computed as:[22]

$D = \sqrt{[(x_r - x_o)^2 + (y_r - y_o)^2]}$ *... (Eq. 12)*

Collision avoidance is maintained when D > D_safe. Whenever an obstacle enters the safety region, the optimization algorithm generates an alternative trajectory. Hybrid swarm approaches demonstrate superior performance because they combine fast convergence with adaptive search.

### 2.10. Performance Evaluation Metrics

Navigation algorithm effectiveness is evaluated using:[23]

- Path Length: $L = \Sigma \sqrt{[(x_{i+1}-x_i)^2 + (y_{i+1}-y_i)^2]}$ (Eq. 13) — shorter trajectories indicate better efficiency.
- Computational Time: Lower execution time enables real-time deployment.
- Energy Consumption: Efficient algorithms reduce power usage and extend battery life.
- Success Rate: Percentage of completed navigation tasks without collisions.
- Convergence Speed: Faster convergence ensures rapid decision-making in dynamic settings.

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## 3. Simulation Results

The comparative performance values in Table 4 are obtained from a synthesis of the published benchmark results reported in the literature (see References [1], [3], [6], [14], [22]). The reported metrics are based on standardized simulation settings: a MATLAB-implemented dynamic environment with 20 obstacles (10 static, 10 moving) in a 100x100 m grid, and each algorithm is evaluated over 50 independent runs. These values are presented as a representative literature-based comparison and are meant to indicate relative algorithm behavior and are not original experimental data. Future work includes an independent empirical validation on a physical robotic testbed.

Table 4: Simulation Performance Comparison

| Algorithm | Path Length (m) | Exec. Time (ms) | Success Rate (%) | Energy (J) | Iterations | Notes |
|---|---|---|---|---|---|---|
| **PSO** | 48.2 | 120 | 91.5 | 34.2 | 80 | Fast but can trap in local optima |
| **ACO** | 46.7 | 380 | 94.3 | 35.8 | 200 | High accuracy, slower execution |
| **GWO** | 45.1 | 210 | 96.8 | 30.5 | 120 | Best overall balance |
| **ABC** | 47.3 | 290 | 93.2 | 33.1 | 150 | Good diversity, moderate speed |
| **PSO-GWO** | 44.0 | 180 | 97.9 | 28.7 | 100 | Best path quality & efficiency |
| **A* (baseline)** | 52.6 | 55 | 82.0 | 42.1 | N/A | Fast but poor in dynamic env. |

Results indicate that GWO achieves the best single-algorithm performance with a 96.8% success rate and the lowest energy consumption (30.5 J). The PSO-GWO hybrid further improves all metrics, achieving a 97.9% success rate with a path length of 44.0 m. PSO remains the fastest per iteration but is outperformed in accuracy by GWO and ACO.

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## 4. Discussion

The results of the comparative study and simulations provide some important insights about the suitability of different swarm intelligence algorithms for dynamic navigation applications.

### 4.1 Why GWO is Most Effective in Some Situations

The main reason for the better performance of the Gray Wolf Optimizer in dynamic conditions is its hierarchical leadership structure. The alpha-beta-delta-omega hierarchy prevents premature convergence, as the residual population is forced to be led by the best solutions. The mathematical coefficient vectors A and C allow GWO to keep fast convergence and escape from the local optima by dynamically switching between exploration ($|A| > 1$) and exploitation ($|A| < 1$). GWO's adaptive balance between global search and local refinement works very well in scenarios with many moving impediments requiring regular re-planning of the path.

### 4.2 Why PSO Is Faster but Not As Accurate

PSO exhibits the minimum execution time per iteration due to its simple velocity-position update that does not require processing overhead. However, the lack of a mechanism to avoid premature convergence causes PSO to often get stuck in local optima especially when the number of moving obstacles increases. This tendency is left little control due to the inertia weight w. PSO is still very good for time critical applications where approximations are allowed . However, GWO or hybrid methods are more appropriate for high accuracy situations.

### 4.3 When to Use the Hybrid Algorithms?

For speed and accuracy, hybrid algorithms like PSO-GWO are recommended. PSO-GWO combines the strong exploration ability of GWO and the fast convergence speed of PSO. The results in Table 4 show that PSO-GWO has the minimum energy consumption (28.7 J), minimum path length (44.0 m) and maximum success rate (97.9%). Hybrid techniques are particularly useful in large-scale environments with high obstacle density, multi-agent systems requiring coordination, UAV navigation with strict energy constraints, and real-time applications requiring both speed and reliability.

The choice between single-algorithm and hybrid approaches should consider the degree of dynamism of the environment, real-time limitations and processing resources.

### 4.4. Joint Action of Several Agents

Many modern navigation systems consist of several independent agents operating simultaneously. Cooperation between multiple agents enhances fault tolerance, area coverage and task efficiency. Communication between agents allows to exchange information about barrier locations, target co-ordinate, path quality and environmental changes. Applications include intelligent transportation networks, search and rescue operations, autonomous drone swarms and warehouse robots.

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### 4.5 Applications of Swarm Intelligence Based Navigation

Swarm intelligence based navigation has been successfully applied in many fields. Autonomous mobile robots use smart navigation to automate warehouses. UAV Drone Swarm using Optimization Algorithms for Tracking and Monitoring Smart cars drive safely with dynamic path planning. Multi-robot systems are used to search for victims in dangerous situations. Agricultural robots are used in precision farming and crop monitoring. Planetary navigation based on swarms is advantageous for the space exploration missions.

## 5. Conclusion

This study examined the use of swarm intelligence techniques to the design of navigation systems for dynamic environments. The PSO, ACO, GWO and ABC principles, that have special advantages in exploration, convergence and obstacle avoidance, are focused in the study. A comparative analysis shows that GWO exhibits the best single algorithm compromise between accuracy and convergence, while PSO excels in speed. In all of the considered criteria, hybrid methods such as PSO-GWO are better than standalone algorithms.

The proposed four-layer design integrates motion control, swarm optimization, AI-based processing, and ambient sensing. The simulation results show that the hybrid swarm intelligence brings a significant improvement on the navigation performance under dynamic scenarios in comparison with conventional methods. Future research directions can include the integration of deep learning, edge computing, and 6G communication to reach higher levels of autonomy and intelligence in the next generation of autonomous systems.

# References

1. Y. Liu, H. Zhang, and X. Wang, "An improved particle swarm optimization approach for dynamic path planning in mobile robots," IEEE Access, vol. 8, pp. 189672–189684, 2020.
2. J. Zhang, W. Li, and Y. Chen, "Hybrid ant colony optimization for autonomous navigation in dynamic environments," Applied Sciences, vol. 10, no. 22, pp. 1–18, 2020.
3. A. Singh, R. Kumar, and P. Sharma, "Grey wolf optimization-based path planning for mobile robots," Robotics and Autonomous Systems, vol. 135, pp. 1–12, 2021.
4. M. Chen, Y. Hao, and K. Hwang, "Multi-agent swarm intelligence for autonomous navigation systems," Future Generation Computer Systems, vol. 117, pp. 360–372, 2021.
5. F. Alharthi, A. Alsubaie, and M. Alotaibi, "Swarm intelligence techniques for autonomous systems: A comprehensive review," Sensors, vol. 21, no. 15, pp. 1–30, 2021.
6. S. Kumar, V. Sharma, and R. Gupta, "Hybrid PSO-GWO optimization for real-time path planning," Expert Systems with Applications, vol. 181, pp. 115–130, 2021.

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**ISSN: 2320-088X**
**Impact Factor: 7.056**

**7.** L. Wang, X. Zhao, and J. Huang, "Reinforcement learning enhanced swarm intelligence for dynamic navigation," IEEE Access, vol. 10, pp. 23451–23465, 2022.
**8.** M. Ahmed, H. Ibrahim, and S. Hassan, "Swarm-based UAV navigation in dynamic environments," Drones, vol. 6, no. 12, pp. 1–20, 2022.
**9.** P. Roy and D. Das, "Particle swarm optimization for obstacle avoidance in autonomous robots," Applied Intelligence, vol. 52, no. 8, pp. 9023–9040, 2022.
**10.** T. Zhao and K. Li, "Ant colony optimization for adaptive path planning in mobile robotics," Robotics, vol. 11, no. 5, pp. 1–18, 2022.
**11.** H. Li, Z. Xu, and J. Wang, "Grey wolf optimizer applications in autonomous vehicle navigation," Mathematics, vol. 10, no. 14, pp. 1–22, 2022.
**12.** S. Verma and A. Gupta, "Artificial bee colony algorithm for intelligent robot navigation," Applied Sciences, vol. 12, no. 16, pp. 1–19, 2022.
**13.** M. Khan, A. Rehman, and T. Mahmood, "Multi-robot cooperation using swarm intelligence," Sensors, vol. 23, no. 4, pp. 1–25, 2023.
**14.** X. Wu and Y. Sun, "Dynamic obstacle avoidance using hybrid swarm optimization," IEEE Access, vol. 11, pp. 54233–54247, 2023.
**15.** B. Patel and S. Joshi, "Path planning optimization in dynamic environments using swarm-based methods," Engineering Applications of Artificial Intelligence, vol. 120, pp. 1–15, 2023.
**16.** J. Kim and H. Park, "Real-time navigation framework for autonomous mobile robots," Electronics, vol. 12, no. 11, pp. 1–20, 2023.
**17.** R. Almutairi and A. Alotaibi, "Swarm intelligence and machine learning integration for autonomous navigation," Machines, vol. 11, no. 8, pp. 1–22, 2023.
**18.** Z. Yang, Q. Liu, and F. Zhou, "Collaborative multi-agent path planning based on swarm intelligence," IEEE Access, vol. 12, pp. 24561–24578, 2024.
**19.** M. Hassan and K. Mahmood, "Advanced swarm optimization techniques for autonomous systems," Applied Intelligence, vol. 54, no. 3, pp. 2211–2230, 2024.
**20.** A. Nouri, H. Salem, and M. Abdullah, "Hybrid intelligent navigation systems in dynamic environments," Sensors, vol. 24, no. 6, pp. 1–26, 2024.
**21.** F. Ibrahim and M. Rashid, "Artificial intelligence and swarm-based navigation: Recent advances," Electronics, vol. 13, no. 5, pp. 1–24, 2024.
**22.** K. Ahmed and Y. Zhao, "Performance evaluation of swarm intelligence algorithms for path planning," IEEE Access, vol. 12, pp. 99121–99139, 2024.
**23.** Hasan, I. N. (2022). The extent to which companies adhere to disclosure controls in accordance with the requirements of IAS in light of Covid-19. Journal of Research in Social Science and Humanities, 2(2), 41-46.

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