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Intelligent control and path planning of mobile robots: a review of conventional and artificial intelligence-based approaches

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ABSTRACT

Intelligent control and path planning are essential capabilities that enable mobile robots to navigate autonomously, avoid obstacles, and perform tasks in structured and unstructured environments. Conventional approaches, including graph-search algorithms, feedback control, and artificial potential fields, provide established solutions with relatively predictable computational behavior. However, their performance can deteriorate in complex environments involving dynamic obstacles, incomplete information, and changing operating conditions. Artificial intelligence (AI)-based approaches, such as fuzzy logic, neural networks, genetic algorithms, particle swarm optimization, and ant colony optimization, offer alternative mechanisms for learning, adaptation, and search optimization. This review examines the principles, applications, strengths, and limitations of conventional and AI-based approaches using publications available up to 2015. It also discusses hybrid strategies and identifies research challenges for developing reliable and computationally efficient mobile robot navigation systems.

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1. INTRODUCTION

Autonomous mobile robots are increasingly expected to operate in environments where predefined movement instructions are insufficient to guarantee successful navigation. Their tasks may involve reaching a destination, avoiding static and moving obstacles, responding to unexpected environmental changes, and maintaining safe motion. These requirements make control and path planning two closely related problems in mobile robotics. A robot may generate a theoretically suitable route, but inaccurate motion control or inadequate obstacle detection can prevent it from following that route successfully.

Conventional control and planning methods have provided important foundations for autonomous navigation. Algorithms such as Dijkstra's method and A* search can identify routes through graph-based environmental representations, while feedback controllers regulate the robot's physical movement. Artificial potential fields and the dynamic window approach (DWA) provide mechanisms for local obstacle avoidance and motion selection. Nevertheless, conventional methods can encounter limitations when the environment is uncertain, the robot's model is inaccurate, or the number of possible navigation decisions becomes large.

Artificial intelligence offers additional capabilities for addressing these limitations. Fuzzy logic can represent approximate reasoning, neural networks can learn relationships between sensor inputs and control actions, and evolutionary algorithms can search for suitable paths through complex solution spaces. These methods are particularly relevant when precise mathematical models or complete environmental information are difficult to obtain. This review compares conventional and AI-based approaches, examines their integration, and identifies the research issues that influence their practical implementation.

2. CONVENTIONAL CONTROL AND PATH PLANNING APPROACHES

Conventional mobile robot navigation generally separates global path planning from local motion control. Global planning determines a route from an initial position to a target using an environmental map or

graph representation. Local control then regulates the robot's movement and responds to nearby obstacles or deviations from the planned route. This separation simplifies system design, although effective navigation requires continuous coordination between both functions.

Graph-search algorithms are widely used for global path planning because they provide systematic procedures for exploring possible routes. Dijkstra's algorithm identifies shortest paths in weighted graphs, while A* improves search efficiency by incorporating heuristic information about the remaining distance to the goal. Hart *et al.* [1] established the theoretical basis of heuristic minimum-cost path searching, which became an important foundation for A* applications. These algorithms are useful in known environments, but their performance depends on map quality, graph resolution, and the computational cost of searching large spaces.

Artificial potential fields provide a different approach to navigation by representing the target as an attractive influence and obstacles as repulsive influences. The robot selects its movement according to the combined influence of these fields, allowing relatively direct responses to environmental information. Khatib [2] demonstrated the application of artificial potential fields to real-time obstacle avoidance for manipulators and mobile robots. Despite their simplicity and responsiveness, potential-field methods can suffer from local minima, oscillatory behavior, and difficulties in navigating narrow passages.

The Dynamic Window Approach provides a more motion-oriented method for local planning and obstacle avoidance. Fox *et al.* [3] developed a method that evaluates feasible velocity commands according to the robot's dynamic constraints and its ability to stop safely before reaching an obstacle. This approach connects path planning with practical control because candidate trajectories are evaluated using physically achievable robot motions. Its effectiveness depends on the accuracy of the robot model, the quality of obstacle measurements, and the computational resources available for evaluating candidate velocities.

Conventional feedback control remains important for executing the movement generated by a planning algorithm. A controller compares the desired motion with measured robot behavior and adjusts motor commands to reduce tracking errors. Proportional-integral-derivative control is commonly used because of its relatively simple implementation and practical tuning procedures. However, fixed controller parameters may not provide satisfactory performance when payloads, friction, wheel slip, or environmental conditions change significantly.

3. ARTIFICIAL INTELLIGENCE-BASED CONTROL AND PLANNING

AI-based approaches extend conventional navigation by introducing learning, approximate reasoning, or optimization mechanisms. Unlike methods that depend primarily on explicit geometric models, some AI techniques can derive decisions from sensor data, experience, or population-based searches. Their main objective is to improve adaptability when the environment or robot behavior cannot be represented accurately through simple analytical models. However, their practical effectiveness depends on training quality, parameter selection, computational requirements, and the reliability of the resulting decisions.

3.1. Fuzzy logic control

Fuzzy logic is useful when navigation decisions involve uncertain or imprecise sensor information. Instead of relying exclusively on exact numerical thresholds, a fuzzy controller uses linguistic concepts such as near, far, left, and right to represent environmental conditions. These concepts are combined through rule-based reasoning to determine suitable control actions. Saffiotti [4] discussed the use of fuzzy logic in autonomous robot navigation and demonstrated its relevance to reasoning under uncertainty.

Fuzzy controllers can be particularly useful for obstacle avoidance because they allow several sensor measurements to influence steering and speed decisions. Their rule-based structure can also make the decision process easier to interpret than some learning-based methods. Nevertheless, controller performance depends strongly on the design of membership functions and inference rules. A poorly designed rule base may produce inconsistent movement or inadequate responses in situations that were not considered during development.

3.2. Artificial neural networks

Artificial neural networks provide a learning-based alternative for mapping sensory information to navigation or control decisions. A network can be trained using examples of robot movement, environmental observations, or desired control responses. Thrun [5] investigated learning-based mobile robot navigation, demonstrating the potential of learning methods for acquiring navigation behavior. Neural networks can represent nonlinear relationships that are difficult to describe using conventional control rules, although their performance depends on training data and the similarity between training and operating environments.

The principal advantage of neural networks is their ability to learn complex input-output relationships without requiring a complete analytical model of the environment. They can support obstacle recognition, sensor interpretation, movement prediction, and navigation decision-making. However,

insufficient training examples or significant changes in environmental conditions can reduce prediction accuracy. Their internal decision processes may also be difficult to interpret, which creates additional challenges when safety and predictable behavior are essential.

3.3. Genetic algorithms and particle swarm optimization

Evolutionary and swarm-based algorithms approach path planning as an optimization problem. Genetic algorithms generate candidate solutions and improve them through selection, crossover, and mutation operations. Liu *et al.* [6] applied a tailored genetic algorithm to mobile robot path planning involving multiple target locations. Such methods can explore complex solution spaces and optimize several path characteristics, although their performance depends on population size, fitness-function design, and parameter selection.

Particle swarm optimization uses a population of candidate solutions that progressively adjusts its search behavior based on individual and collective experience. Kennedy and Eberhart [7] introduced the particle swarm optimization framework for nonlinear optimization problems. In mobile robotics, this approach can be adapted to search for routes that balance path length, obstacle clearance, and other planning objectives. Nevertheless, swarm-based optimization may require many iterations and can converge prematurely when the search parameters or objective function are poorly selected.

3.4. Ant colony optimization

Ant colony optimization is inspired by the cooperative path-searching behavior of biological ant colonies. Candidate solutions are constructed through artificial agents that exchange indirect information using a pheromone-based mechanism. Dorigo and Gambardella [8] developed the ant colony system as a cooperative optimization method for combinatorial problems. For mobile robot path planning, the method can be adapted to identify promising routes through graph-based representations, although its computational cost may increase in large or frequently changing environments.

4. COMPARATIVE ANALYSIS OF NAVIGATION APPROACHES

Conventional and AI-based methods provide different advantages depending on the operating environment and navigation requirements. Conventional graph-search methods are generally suitable for structured environments with reliable maps, whereas reactive approaches can respond to nearby obstacles without requiring complete global information. AI-based methods provide additional flexibility through learning and optimization, but they may require extensive parameter tuning or computational resources. Khaksar *et al.* [9] reviewed mobile robot path-planning methods for unknown environments and highlighted the importance of selecting techniques according to environmental conditions and planning requirements.

Table 1 compares representative conventional and AI-based approaches according to their main functions, advantages, and limitations. The comparison emphasizes that algorithm selection should consider more than path length or computational speed. Factors such as adaptability, environmental uncertainty, real-time response, and implementation complexity also influence navigation performance. These characteristics are particularly important when mobile robots operate in environments containing dynamic obstacles or incomplete environmental information.

Table 1. Comparison of conventional and AI-based mobile robot navigation methods

Method	Category	Main strengths	Main limitations
Dijkstra and A*	Conventional search	Systematic global route search; predictable behavior	Dependence on maps; search cost in large spaces
Artificial potential fields	Conventional/reactive	Simple implementation; rapid obstacle response	Local minima and oscillation
Dynamic window approach	Conventional/local planning	Considers velocity and stopping constraints	Depends on motion modeling and computation
Fuzzy logic	AI-based reasoning	Handles imprecise sensor information; interpretable rules	Rule and membership-function design
Neural networks	AI-based learning	Learns nonlinear sensor-to-action relationships	Requires representative training data
Genetic algorithms	Evolutionary optimization	Flexible search for complex paths and objectives	Computational cost and parameter sensitivity
Particle swarm optimization	Swarm optimization	Population-based search and relatively simple implementation	Premature convergence and parameter dependence
Ant colony optimization	Swarm optimization	Cooperative search for promising graph routes	Iterative computation and convergence time

Table 1 indicates that conventional and AI-based approaches should not be viewed as mutually exclusive alternatives. Graph-search methods can provide global guidance, while reactive controllers can handle immediate obstacles and motion constraints. AI-based methods can improve decision-making when sensor information is uncertain or when route optimization involves several competing objectives. A suitable navigation architecture can therefore combine the strengths of different methods rather than relying on a single algorithm.

5. HYBRID INTELLIGENT NAVIGATION

Hybrid navigation combines conventional algorithms with AI-based techniques to address limitations that may arise when individual methods are used independently. For example, A* can generate a global route, while fuzzy logic or a potential-field controller can modify local movement in response to nearby obstacles. Genetic algorithms or particle swarm optimization can also be used to improve route selection according to multiple criteria. Khaksar *et al.* [9] discuss hybrid planning approaches as part of the broader range of methods for navigation in unknown environments.

The main advantage of hybrid systems is their ability to divide navigation into complementary functions. Conventional planning can provide structured route guidance, while intelligent controllers can respond to uncertainty and changing conditions. This arrangement can improve flexibility without requiring every navigation function to be learned or optimized from scratch. However, integration introduces additional design challenges because different algorithms may produce conflicting decisions or operate at different update rates.

A practical hybrid architecture should therefore establish clear responsibilities between global planning, local planning, and motion control. The global planner should consider the overall route and destination, while the local planner should respond to nearby obstacles and short-term changes. The motion controller should ensure that the selected movement is physically achievable and consistent with the robot's dynamic limitations. Such coordination is necessary to prevent a locally safe action from creating an inefficient or infeasible global route.

6. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Despite substantial progress before 2016, reliable navigation in unknown and dynamic environments remained a major research challenge. Conventional algorithms can become inefficient when maps are large or environmental information changes frequently. AI-based methods can improve adaptability, but their performance may be difficult to guarantee under unfamiliar operating conditions. Khaksar *et al.* [9] identify unknown environments and motion-planning complexity as important issues in mobile robot research.

Another challenge concerns the relationship between navigation performance and computational resources. A method that generates high-quality paths may still be unsuitable for a mobile robot with limited processing capability or strict real-time requirements. Learning-based methods also require appropriate training and validation before deployment in environments where incorrect decisions may cause damage or safety risks. Future research should therefore evaluate algorithms using consistent performance measures, including path length, execution time, collision avoidance, adaptability, and computational cost.

The integration of intelligent planning with reliable control is also an important direction for future development. A robot must not only identify a suitable route but also follow it accurately despite disturbances, mechanical uncertainty, and sensor limitations. Hybrid systems should be evaluated through realistic experiments rather than relying exclusively on simulations or isolated algorithm comparisons. More systematic testing would help establish whether improvements in planning quality translate into dependable navigation in practical applications.

7. CONCLUSION

Conventional and AI-based approaches provide complementary solutions to the intelligent control and path-planning problems of mobile robots. Graph-search algorithms offer systematic global planning, while artificial potential fields and the dynamic window approach support local obstacle avoidance and motion selection. Fuzzy logic, neural networks, genetic algorithms, particle swarm optimization, and ant colony optimization introduce reasoning, learning, and search capabilities that can improve adaptability in complex environments. Each method nevertheless has limitations involving computational cost, parameter sensitivity, model accuracy, or environmental uncertainty.

The review demonstrates that reliable autonomous navigation requires coordinated planning, control, and environmental perception rather than dependence on a single algorithm. Hybrid architectures provide a promising approach by combining the predictable behavior of conventional methods with the

adaptability of AI-based techniques. Their successful implementation depends on appropriate algorithm selection, effective coordination, and validation under realistic operating conditions. Continued research into robust, efficient, and explainable intelligent navigation is essential for expanding the practical capabilities of autonomous mobile robots.

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