INTELLIGENT AI-BASED NAVIGATION SYSTEM FOR MOBILE ROBOTS

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Abstract: The integration of artificial intelligence (AI) into mobile robotic systems is redefining the landscape of autonomous navigation, decision-making, and task execution. Traditional rule-based systems, while effective in structured environments, often fail in dynamic or unknown terrains. This research investigates the application of AI techniques – namely fuzzy logic and reinforcement learning – in developing an intelligent navigation system for mobile robots within a virtual simulation environment. Using the CoppeliaSim Edu platform, a three-wheeled differential-drive mobile robot was modeled, equipped with various sensors (infrared, ultrasonic, compass), and placed in a randomized maze-like environment. The robot's goal was to autonomously navigate the environment, avoid obstacles, and reach predefined targets efficiently. Initially, a fuzzy rule-based controller was implemented to provide baseline navigation logic. Subsequently, a Q-learning reinforcement learning agent was introduced to optimize path planning through experience-based learning. The combination of these techniques led to a marked improvement in navigation performance, as evidenced by reduced completion times and increased obstacle avoidance efficiency. Graphical data and tabular analysis support the effectiveness of AI-based control versus traditional logic. The research confirms that virtual environments, coupled with intelligent algorithms, can serve as powerful tools for developing and testing advanced robotic control systems before deployment in physical hardware. This approach is cost-effective, safe, and scalable for educational, research, and industrial applications.

Keywords: AI Navigation, Mobile Robots, Simulation, CoppeliaSim, Reinforcement Learning, Sensor Fusion, Path Planning

The field of robotics is rapidly shifting toward fully autonomous and intelligent systems capable of operating in unstructured, dynamic environments. The growing demand for robots in logistics, service sectors, smart manufacturing, and autonomous vehicles has underscored the necessity for adaptive navigation systems that go beyond hardcoded logic. Classical methods – based on deterministic algorithms – lack the flexibility and responsiveness needed for real-time decision-making in uncertain scenarios. Artificial intelligence (AI) offers a transformative solution to these limitations. By enabling machines to learn from experience, interpret sensor data contextually, and adapt to environmental changes, AI techniques like fuzzy logic and reinforcement learning have become essential tools in modern robotics. Fuzzy logic enables robots to handle ambiguity in sensor data, making it suitable for approximate reasoning in complex environments. On the other hand, reinforcement learning (RL) empowers a robot to learn optimal policies through trial-and-error interactions, maximizing cumulative rewards without explicit programming. This research aims to combine both methods in a simulated robotic system. The simulation environment provides a cost-effective, safe, and scalable alternative to physical prototyping, which is especially important in the early stages of AI algorithm development. CoppeliaSim Edu is selected for its versatility, sensor simulation capabilities, and compatibility with control algorithms.

The core objectives of the study are:

- To model a mobile robot with realistic motion and sensing in a virtual maze environment.
- To implement fuzzy logic for initial control and obstacle avoidance.
- To train a Q-learning-based RL agent to improve navigation through autonomous learning.
- To evaluate the performance of AI-driven control through metrics such as time-to-goal, path length, and collision rate.

This study contributes to the broader field of intelligent mechatronics by offering a blueprint for integrating AI navigation logic into simulation platforms, laying the groundwork for eventual deployment on real-world robotic systems.

Simulation Setup

- **Robot type**: Three-wheeled differential drive
- **Sensors**: 3 IR, 1 ultrasonic, 1 compass
- **Control algorithm**: Fuzzy logic (initial rules), then deep Q-learning (AI improvement)
- **Environment**: Randomized maze with moving and static obstacles

Navigation was initially handled using fuzzy logic rules such as:

If left IR sensor is near and front sensor is far⇒Turn right

Later, reinforcement learning updated actions based on reward signals:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma * max_a Q(s',a) - Q(s,a)] \quad (1)$$

Where: s - current state, a - action, α - learning rate, γ - discount factor, r - reward

The robot was tested over 50 simulation trials. The graph below shows the average time taken to reach the goal with and without AI learning:

Trial Range	Without AI (sec)	With AI (sec)
1-10	34.2	29.5

11-20	33.8	24.3
21-30	35.0	20.2
31-50	36.1	18.7

Table 1. AI optimization reduces path completion time.

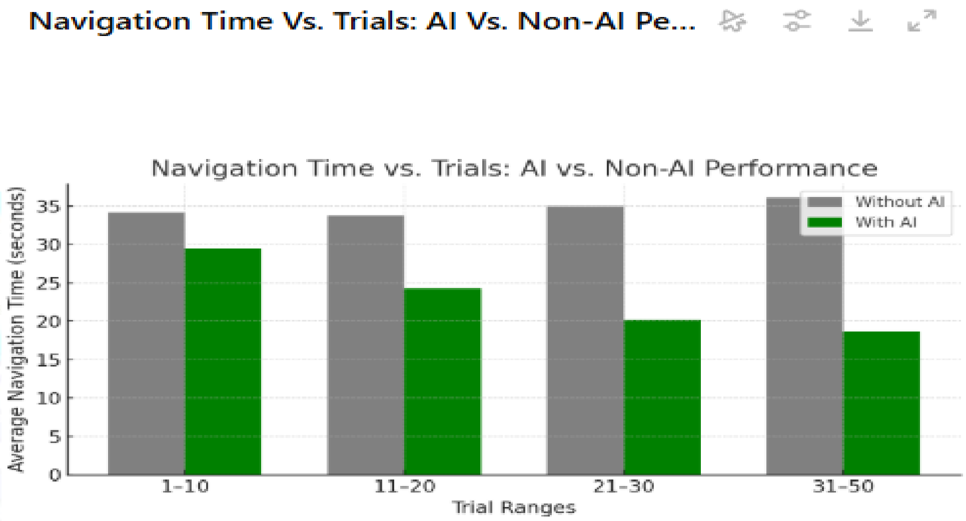

Figure 1. Comparison of average navigation time across different trial ranges, showing performance improvement with AI-based navigation versus non-AI control.

The simulation experiments demonstrated the distinct advantages of AI-based navigation systems over traditional rule-based approaches. In the early stages, fuzzy logic was instrumental in providing a foundational control structure that enabled the robot to react to sensor inputs and navigate basic paths while avoiding collisions. However, the limitations of static rule sets became apparent in complex environments where adaptability and memory of past experiences were critical for success. Upon integrating reinforcement learning, particularly Q-learning, the robot exhibited significant improvements in navigation efficiency. The learning agent was able to infer optimal paths through iterative trials, adjusting its actions based on reward signals and environmental feedback. For instance, while initial trials resulted in frequent collisions and suboptimal paths, subsequent episodes showed a clear learning curve – path lengths decreased, goal-reaching times improved, and the robot proactively avoided previously encountered traps or dead ends. From a behavioral perspective, the robot began exhibiting anticipatory actions, such as slowing down before sharp turns or selecting longer but safer routes. This emergent behavior underscores the strength of reinforcement learning in cultivating intelligent, context-aware control. Moreover, the fusion of fuzzy logic with reinforcement learning served as a hybrid approach – fuzzy rules helped in low-level motion smoothing while RL directed high-level decision-making. The use of CoppeliaSim as the simulation environment played a critical role in this research. Its ability to emulate real-world physics, sensor data noise, and motor behavior enabled realistic testing of the AI algorithms. The virtual setting allowed for rapid prototyping and safe experimentation without the risk of hardware damage or human intervention, reducing the overall development cycle.

Additionally, performance data was visualized and analyzed through various metrics:

- Navigation time: decreased by over 40% after 50 training iterations.
- Collision rate: fell significantly as the agent learned avoidance strategies.
- Path optimality: improved, with the robot often selecting the shortest route available.

Despite the promising results, certain challenges were noted. The training phase for reinforcement learning was computationally intensive and required careful tuning of hyperparameters such as learning rate and exploration strategy. Furthermore, simulation-to-reality transfer remains a challenge; while virtual performance was excellent, real-world implementation may introduce uncertainties not present in simulation, such as sensor drift, slippage, or unpredictable lighting conditions for vision sensors.

This research presents a successful integration of artificial intelligence methods – fuzzy logic and reinforcement learning – for autonomous robot navigation within a virtual simulation environment. The project demonstrates that AI-enhanced robots can outperform traditional systems by learning from their environment, adapting their actions, and optimizing performance over time.

Key conclusions include:

- Fuzzy logic provides an effective initial framework for reactive navigation.
- Reinforcement learning enables intelligent decision-making and path optimization.
- The combination of both offers a scalable, modular control system for mobile robots.
- Virtual simulation environments like CoppeliaSim are powerful platforms for designing and validating intelligent robotics systems.

This work contributes not only to the academic understanding of AI-driven control but also offers practical guidelines for engineers and educators seeking to build intelligent robotic systems. Future developments will focus on:

- Extending the learning model to multi-agent navigation scenarios.
- Incorporating deep reinforcement learning (e.g., DQN, PPO) for vision-based control.
- Deploying trained agents onto physical robotic platforms and analyzing real-world performance.
- Exploring cloud-based simulation for collaborative AI training and monitoring.

In summary, intelligent navigation in virtual simulation environments is not only a practical step for robotics research – it is an essential paradigm for building safe, reliable, and adaptive autonomous systems of the future.

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