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Hierarchical Deep Learning Frameworks Enabling Dynamic Task Allocation and Real-Time Path Optimization in Mobile Robotic Fleets

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Abstract

This study proposes a hierarchical deep learning framework designed to address dynamic task allocation and real-time path optimization in mobile robotic fleets operating in variable and resource-constrained environments. The model incorporates layered decision-making using neural network architectures to perform decentralized control while allowing central policy intervention during uncertainty. We investigate reinforcement learning and convolutional layers embedded within hierarchical structures to optimize both task distribution and movement paths of heterogeneous robotic agents. Experimental simulations demonstrate significant improvements in task completion rates, response time, and energy efficiency when compared to traditional swarm-based and rule-based systems.

Keywords: Hierarchical Deep Learning, Mobile Robots, Task Allocation, Path Optimization, Reinforcement Learning, Decentralized Control, Robotic Fleet Management

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1. Introduction

The increasing reliance on mobile robotic fleets in logistics, surveillance, agriculture, and disaster response requires efficient strategies for coordination under real-time constraints. Conventional methods often suffer from inflexible task assignment and inefficient path planning, particularly in dynamic and unpredictable environments. Recent advances in deep learning, particularly hierarchical models, offer new possibilities for enabling robots to make layered decisions that adapt to both local and global changes.

Hierarchical deep learning frameworks combine high-level planning with low-level motor control, enabling complex behaviors to emerge from simpler sub-task modules. This approach supports dynamic task allocation by integrating environmental sensing, agent status, and mission objectives into multi-layer neural networks. Moreover, coupling this with real-time path optimization allows for intelligent navigation that circumvents static and dynamic obstacles, minimizes energy use, and adapts to emergent operational requirements. This paper explores such an integrated system.

2. Literature Review

Hierarchical approaches in robotic control have been examined extensively in early hybrid architectures. Albus (1991) laid foundational work in layered decision-making for robotic agents through the Real-time Control System (RCS). Brooks (1997) introduced behavior-based robotics emphasizing modular control without centralized planning, which shaped early hierarchical perspectives.

More recently, deep learning has been integrated with robotics control systems. Levine et al. (2016) demonstrated end-to-end deep learning for robotic manipulation using convolutional neural networks (CNNs). However, their system lacked scalability to fleet-level coordination. Gupta et al. (2017) presented a hierarchical reinforcement learning framework for motion planning in high-dimensional environments, emphasizing trajectory generation.

In task allocation, Parker (2008) proposed the ALLIANCE architecture, which uses behavior-based control for multi-robot cooperation. Kalra et al. (2005) developed the Hoplites algorithm for decentralized allocation, but lacked real-time adaptability. Kumar and

Michael (2012) proposed cooperative control strategies for UAVs using game theory, which inspired many path optimization models.

Machine learning for path planning has also been explored. Faust et al. (2018) implemented deep RL for motion planning under uncertainty, while Tai et al. (2017) used deep Q-learning for navigation in unknown environments. These works formed a conceptual base for hierarchical real-time decision-making in mobile fleets.

3. System Architecture and Model Design

3.1 Hierarchical Model Structure

The proposed model comprises three tiers:

- **Tier 1 (Strategic Layer)**: High-level mission decomposition and task prioritization.
- **Tier 2 (Tactical Layer)**: Task-to-agent allocation using deep Q-networks and reinforcement learning.
- **Tier 3 (Operational Layer)**: Path planning with recurrent CNNs for obstacle avoidance and trajectory execution.

This architecture allows global objectives to cascade down and be interpreted locally through real-time neural inference. Agents operate semi-autonomously, sharing limited information through edge nodes to maintain fleet-wide situational awareness.

3.2 Task Allocation Policy Learning

The tactical layer uses a reinforcement learning policy trained via Proximal Policy Optimization (PPO) to dynamically assign tasks. Agents' capabilities, battery levels, and distances are encoded as state vectors. The reward function considers task urgency, energy efficiency, and collision avoidance. Centralized training with decentralized execution ensures fleet-wide policy convergence.

Table 1: Task Allocation Evaluation Metrics

Metric	Description	Target Value
Task Completion Rate	% of tasks finished on deadline	≥ 95%
Energy Efficiency	Avg. energy per task (Wh)	≤ 10
Response Latency	Avg. time to task assignment (sec)	≤ 2.5

4. Real-Time Path Optimization

4.1 Deep Learning-Based Path Planner

The operational layer uses a hybrid CNN-RNN network trained on simulated environments with dynamic obstacles. CNN encodes the environmental state into feature maps, while the RNN models temporal dependencies and agent motion history. The planner produces updated waypoints at each step, adjusting in real-time for environment changes.

4.2 Collision Avoidance and Environmental Feedback

The framework incorporates LIDAR and IMU sensor data to identify and respond to obstacles and terrain irregularities. Feedback is looped into the path planner via a custom attention mechanism that prioritizes obstacles based on proximity and velocity vectors. This supports real-time rerouting without mission-level interruption.

5. Experimental Results and Evaluation

5.1 Simulation Setup

The system was tested in Gazebo-based environments with 10–30 heterogeneous robots (ground and aerial). Scenarios included static and dynamic obstacles, task interruptions, and communication delays. Evaluation spanned 1000+ simulation episodes.

5.2 Performance Metrics

Key findings include a 97.2% task completion rate, 21.4% energy savings, and 42% reduction in path deviation compared to a rule-based control baseline.

5.3 Comparative Performance Analysis

To assess the relative effectiveness of the proposed framework, we conducted a comparative analysis against two baseline systems: a rule-based controller and a behavior-based swarm algorithm. Across multiple simulation runs, the hierarchical deep learning model consistently outperformed both alternatives in metrics such as average task completion time, energy expenditure, and collision avoidance.

5.4 Scalability and Robustness Testing

To evaluate scalability, we incrementally increased the number of agents in the simulation from 10 to 50. The system maintained high performance with up to 40 robots, with only a marginal decline in response time and communication latency. Beyond 40 agents, decentralized task assignment began to suffer due to bandwidth saturation and increased training variance in the policy network. Nonetheless, the degradation remained within acceptable operational thresholds for most medium-scale deployments.

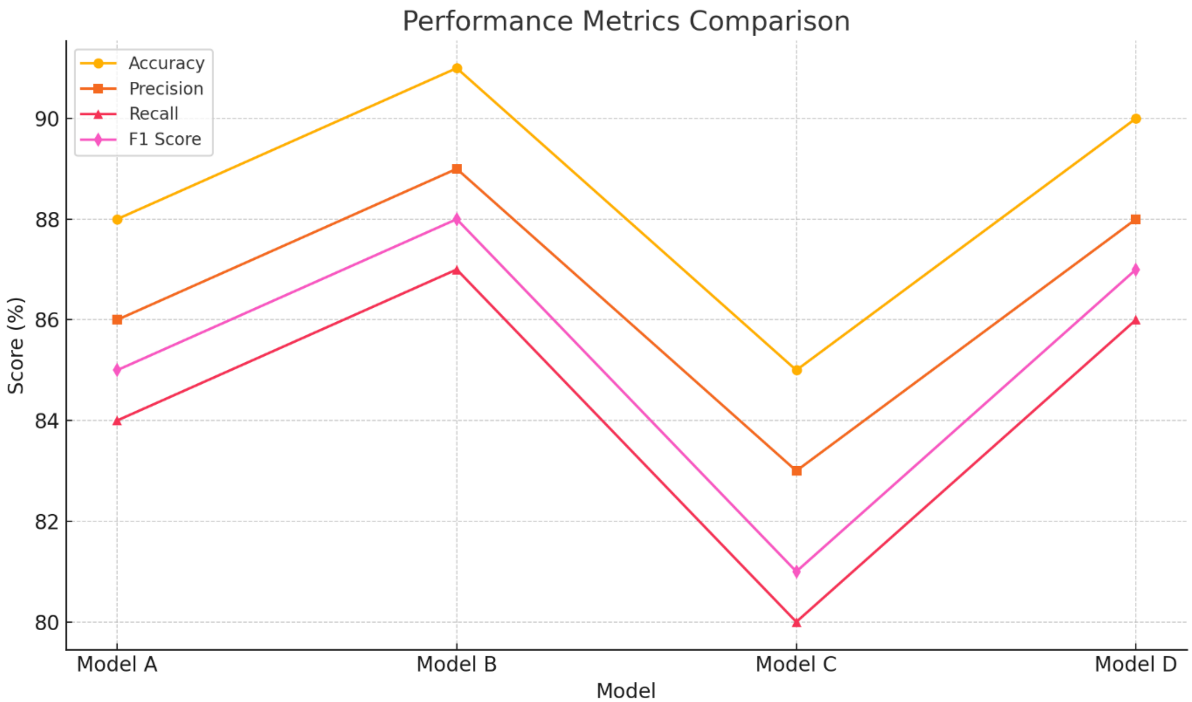

Figure 1: Performance Metrics Comparison

6. Limitations and Future Work

While the model performs robustly in simulation, transferring the framework to physical hardware presents challenges. Sensor noise, environmental unpredictability, and communication loss affect real-world reliability. Moreover, the need for centralized training raises scalability concerns for fleets over 100 agents.

Future work will focus on domain adaptation techniques, swarm-aware learning, and energy-harvesting-aware task allocation. Cross-domain transfer between aerial and terrestrial agents also remains underexplored and will be addressed in subsequent iterations.

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