Hierarchical, Parameter-Based Multi-Agent Architecture for Autonomous Systems Using Reinforcement Learning and Reinforcement Learning from Human Feedback

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***Abstract*—This research introduces a novel hierarchical multi-agent architecture for autonomous systems, where each node in the hierarchy optimizes a specific system parameter using Reinforcement Learning (RL). These node agents are grouped under manager agents responsible for parameter clusters, and a global agent integrates all inputs to execute environment-facing actions. The global agent is aligned with human objectives through Reinforcement Learning from Human Feedback (RLHF). The system enables scalable, modular, and robust behavior through agent-to-agent (A2A) communication across all levels. We evaluate this architecture in dynamic environments, exploring how local optimizations impact global performance, the role of A2A communication, and RLHF's effectiveness in aligning decision-making with human intent.**

***Index Terms*—Hierarchical agents, multi-agent systems, reinforcement learning, RLHF, autonomous systems, modular architecture**

I. Introduction

The rapid advancement of autonomous systems, particularly in domains such as self-driving vehicles, aerial drones, and planetary rovers, demands increasingly sophisticated control architectures capable of handling high-dimensional, dynamic, and uncertain environments. Traditional monolithic control frameworks often fall short in these scenarios due to their limited scalability, interpretability, and adaptability to new tasks or changing environmental dynamics. As a result, there is a growing interest in modular and distributed approaches, particularly those that leverage the learning capabilities of Reinforcement Learning (RL) and the flexibility of Multi-Agent Systems (MAS).

Hierarchical reinforcement learning (HRL) has emerged as a powerful paradigm for decomposing complex tasks into simpler subtasks, allowing agents to learn policies at different levels of abstraction. Simultaneously, multi-agent reinforcement learning (MARL) has demonstrated potential in enabling decentralized coordination and parallel policy learning across agents. However, existing approaches often conflate task hierarchy with agent hierarchy, or lack explicit parameter-based modularity, which can lead to inefficiencies in both learning and execution, particularly in heterogeneous, real-time environments.

This paper proposes a novel architecture that addresses these limitations by introducing a **hierarchical, parameter-centric multi-agent system**. In our framework, the control hierarchy is built from the ground up based on system parameters—each **node agent** is assigned to control or optimize a specific parameter of the environment or the autonomous system. These nodes are organized into logical clusters governed by **manager agents**, which coordinate among related parameters (e.g., navigation parameters, sensor calibration, or actuator control). At the apex lies a **global agent**, responsible for integrating high-level decisions and performing the actual environment-facing actions. Crucially, this global agent is aligned with human values and mission goals using **Reinforcement Learning from Human Feedback (RLHF)**, enabling safe and human-aligned autonomy.

The proposed architecture introduces multiple layers of optimization and coordination:

- **Specialization**: Each node agent becomes an expert in controlling one parameter, simplifying its learning space.
- **Scalability**: New agents can be added or removed without retraining the entire system.
- **Modularity**: Fault isolation, debugging, and updates are localized to specific modules.
- **Inter-agent Communication**: Agents communicate laterally and vertically to ensure that local optimizations contribute to coherent global behavior.

A central research question we address is whether the decomposition of control into parameter-based agents can lead to superior performance in highly dynamic environments compared to flat or task-based hierarchies. Furthermore, we explore how **agent-to-agent (A2A) communication** influences system stability, adaptability, and responsiveness, and how RLHF can align high-level decisions with user intent, even when intermediate agents operate autonomously.

The remainder of this paper is structured as follows: Section II discusses related work in hierarchical RL, multi-agent

coordination, and human-aligned learning. Section III presents the architectural design of our system. Section IV elaborates on the learning algorithms and training protocol. Section V evaluates the framework through simulations in dynamic environments. Section VI offers concluding remarks and outlines future directions, including real-world deployment and integration with safety-critical systems.

II. Related Work

Hierarchical architectures have been pivotal in advancing multi-agent reinforcement learning (MARL) by enabling modular and scalable coordination strategies. One of the foundational works, Cooperative HRL [5], introduced a hierarchical MARL framework where agents learn not only individual subtasks but also the sequence of executing these subtasks and the coordination protocols with teammates. This framework further extends to COM-Cooperative HRL by incorporating a communication layer that allows agents to pay a cost to access other agents' intended actions, thereby optimizing communication efficiency and improving coordination speed.

Building on hierarchical designs, the Hierarchical Multi-Agent Skill Discovery (HMASD) approach [11] proposes a two-level hierarchy with a transformer-based high-level policy that sequentially assigns latent skills to low-level policies. These low-level policies then specialize in both team-level and individual skills, enabling the system to significantly outperform flat MARL baselines on sparse-reward tasks by leveraging structured skill compositions.

Hierarchical frameworks have also been effectively applied in complex real-world inspired problems. For instance, hierarchical swarm control in multi-agent shepherding tasks [3] separates high-level target selection from low-level continuous control, yielding scalable and decentralized coordination among "herder" agents. Similarly, a three-tier hierarchy for multi-UAV air combat [8] assigns leader-follower roles with distinct value functions and policy learning objectives at each layer, facilitating sophisticated cooperative maneuvers in high-dimensional action spaces.

Effective agent-to-agent communication mechanisms are critical for coordination in hierarchical MARL. Cooperative HRL [5] employs communication decisions at cooperative subtasks, balancing communication costs and coordination gains. Hierarchical Consensus MARL (HC-MARL) [4] introduces a multi-layered consensus strategy that blends short-term reactive and long-term strategic observations without explicit message passing, enhancing coordination efficiency in multi-robot cooperation. Additionally, emergent communication protocols learned during training have demonstrated improved robustness and task performance by evolving agent-specific messaging schemes [1].

Human feedback integration has recently gained traction to align agent behavior with human preferences. The MENTOR framework [13] uses reinforcement learning from human feedback (RLHF) at the hierarchical level, where human preferences guide subgoal selection, accelerating learning in sparse-reward environments. Extending this to multi-agent settings, Zhang et al. [12] propose methods to infer Nash-equilibrium policies from offline preference data, addressing challenges such as reward regularization and policy stabilization. Furthermore, human-attention guided MARL [6] incorporates fuzzy logic rules reflecting broad human insights into hierarchical policies, improving coordination among heterogeneous agents in complex environments such as StarCraft.

Scalability and robustness remain key challenges in practical multi-agent deployments. Decentralized scalable RL methods [7] leverage local model learning and agent-level topological decoupling to achieve globally coherent policies in large-scale networks like traffic control and power grids. Resilient MARL algorithms such as DQ-RTS [2] handle unreliable communication and dynamic team membership, maintaining stable performance even under network failures. Applications in cyber defense [9] and swarm confrontation [10] showcase hierarchical MARL's adaptability and interpretability, where task decomposition and uncertainty reasoning enable autonomous, effective decision-making under adversarial and uncertain conditions.

Collectively, these works demonstrate significant advances in hierarchical, modular, and human-aligned MARL frameworks. They highlight how combining layered policy structures, communication protocols, human feedback, and robustness mechanisms can yield scalable, interpretable, and adaptable multi-agent systems suitable for a wide range of complex, real-world applications.

III. System Design

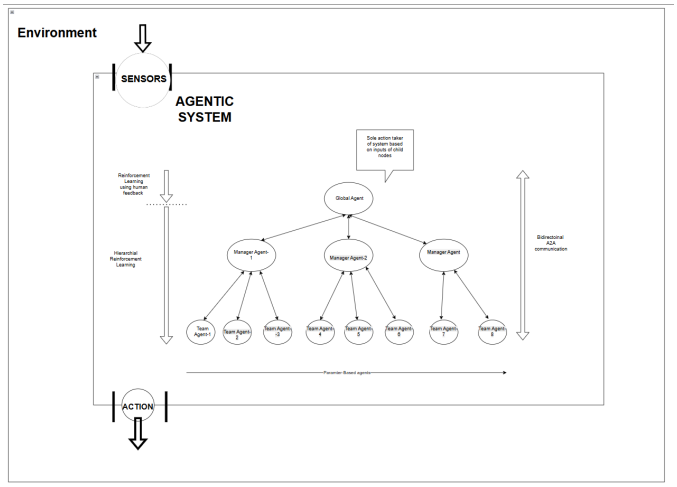

Fig. 1. Tree-Based Hierarchical Agentic System with Reinforcement Learning and RLHF.

A. Overview of the Hierarchical Agentic System

In increasingly complex and dynamic environments — such as deep space exploration, underwater expeditions, and planetary surface missions — the demand for robust, flexible, and intelligent autonomy has never been higher. Traditional

monolithic AI architectures often struggle to scale in such unpredictable conditions due to their rigid, centralized decision-making.

To address these challenges, we propose a Hierarchical Agentic System, designed to imbue autonomous vehicles with both granular specialization and strategic coherence across different mission-critical tasks.

At its core, this system decomposes intelligence across three distinct layers:

- the Global Agent (strategic leadership),
- a network of Modular Agents (domain-specific management),
- and a fleet of Team Agents (task-level specialists).

Each layer is responsible for different scopes of decision-making, ensuring that autonomy is maintained even under sparse communications, environmental uncertainty, or system damage.

This hierarchical architecture is inspired by real-world organizational structures—where executives define vision, managers execute strategies within their domains, and specialists handle operational tasks. Translating this principle into an AI system allows for distributed intelligence, scalable collaboration, and resilient decision-making, crucial for missions operating in remote, dynamic, and often hostile environments.

a) Key Design Goals of the Hierarchical System::

- **Strategic Decomposition:** Break down high-level mission goals into domain-specific operations and then into actionable commands at the parameter level.
- **Parallelized Learning and Adaptation:** Enable agents at different levels to learn and adapt simultaneously via Reinforcement Learning (RL), ensuring continuous optimization across the system hierarchy.
- **Collaborative Autonomy:** Facilitate structured communication and feedback mechanisms to promote collaborative decision-making among agents, enhancing system-wide situational awareness.
- **Resilience and Redundancy:** Allow modular and team-level agents to adapt independently to local failures or environmental perturbations, ensuring robustness in mission-critical operations.
- **Human-in-the-Loop Optimization:** Employ Reinforcement Learning with Human Feedback (RLHF) at the global level to integrate strategic human insights into the learning and adaptation process over time.

In this framework, decision-making is not a singular event but a flow of coordinated intelligence, where each agent acts autonomously within its expertise yet remains aligned with overarching mission objectives. Feedback loops at every level reinforce system learning, allow correction of misaligned behaviors, and dynamically refine both local strategies and global policies.

By deploying a Hierarchical Agentic System, we enable autonomous vehicles—rovers, submarines, drones—to transcend the limitations of static programming, achieving adaptive, resilient, and mission-driven behavior even in the most remote corners of our universe.

B. Players in the System

The strength of the Hierarchical Agentic System lies not only in its layered design but also in the distinct, specialized players that inhabit each layer. Each player—whether strategic, managerial, or operational—contributes unique intelligence to the ecosystem, ensuring that the autonomous vehicle operates as a coherent, adaptive organism.

a) Global Agent (Chief Executive Agent - CEA): At the apex of the hierarchy sits the Global Agent, tasked with overarching mission command. It defines the long-term strategic vision: whether prioritizing energy conservation, maximizing exploration coverage, or executing emergency protocols.

Powered by Reinforcement Learning with Human Feedback (RLHF), the Global Agent continuously refines its strategic choices based on environmental outcomes and expert human interventions. Crucially, it retains the authority to override any decision across the hierarchy in pursuit of mission-critical objectives, serving as the ultimate guardian of system integrity and success.

Key capabilities:

- Strategic mission formulation and real-time re-planning.
- High-level reward shaping for subordinate agents.
- Emergency decision-making and mission override controls.

b) Modular Agents (Domain Managers): Below the Global Agent operate several Modular Agents, each entrusted with mastery over a specific operational domain. These agents embody middle-management intelligence, bridging strategic intent with task-level execution. Every Modular Agent supervises a set of specialized Team Agents, aggregating their feedback and issuing intermediate goals.

Core Modules Include:

- **Motion Control Module Agent (MCMA):** Governs vehicle stability and maneuverability across axes.
- **Environmental Interaction Module Agent (EIMA):** Manages perception, terrain negotiation, and obstacle dynamics.
- **Energy and Resource Management Module Agent (ERMMA):** Optimizes power consumption and resource allocation.
- **Navigation and Path Planning Module Agent (NPPMA):** Crafts optimal trajectories and ensures positional accuracy.
- **Safety and Emergency Module Agent (SEMA):** Maintains vehicle health and triggers fail-safe operations.

Modular Agents not only synthesize complex sensorimotor inputs into actionable insights but also mediate intra-module and inter-module communication, ensuring all decisions remain holistically optimized across the system.

c) Team Agents (Specialists): At the operational frontier are the Team Agents—focused micro-intelligences dedicated to controlling specific vehicle parameters or perceiving specific aspects of the environment.

Examples of Team Agents:

- `PitchControlAgent`, `RollControlAgent`, `YawControlAgent`: Fine-tune vehicle attitude control.
- `ObstacleDetectionAgent`, `TerrainClassificationAgent`: Perform real-time environmental analysis.
- `BatteryManagementAgent`, `CoolingAgent`: Monitor and optimize resource consumption.

Each Team Agent autonomously applies Reinforcement Learning to adapt its local behavior to situational nuances, while remaining tethered to modular objectives through a structured communication and feedback protocol.

Together, these players constitute a distributed, self-optimizing collective intelligence — capable of strategic foresight, adaptive management, and fine-grained environmental interaction, even across the unpredictable theaters of space and ocean exploration.

C. System Workflow and Learning Dynamics

Understanding the operational flow of the Hierarchical Agentic System reveals how autonomy, collaboration, and learning coalesce into mission success.

The system workflow unfolds through a multi-stage, continuous loop:

1) **Strategic Goal Definition (Global Agent)**
   The Global Agent initiates the loop by ingesting mission parameters and environmental updates. It generates strategic directives: goals such as target navigation waypoints, energy optimization thresholds, or safe zones for emergency returns.
   These strategic goals are dynamically re-evaluated over time through RLHF, allowing the Global Agent to recalibrate priorities as new information or human feedback arrives.
2) **Domain-Level Tactical Execution (Modular Agents)**
   Upon receiving strategic intents, each Modular Agent decomposes goals into domain-specific tasks.
   For example:
   - The Motion Control Module Agent translates a "navigate safely" directive into required stability targets across pitch, yaw, and roll.
   - The Environmental Interaction Module Agent processes terrain data to determine necessary vehicle adaptations.
   - The Energy Management Module Agent strategizes energy-saving routes based on real-time power metrics.

   Cross-domain communication ensures that tactical decisions are not made in isolation but are harmonized for overall system optimization.
3) **Localized Action and Feedback (Team Agents)**
   Team Agents then convert tactical tasks into executable parameter adjustments, leveraging their sensor inputs and localized reinforcement learning models.
   Each agent:
   - Selects optimal actions (e.g., adjusting yaw by 3° to avoid an obstacle).
   - Executes movements or adaptations.
   - Monitors immediate outcomes.

   Performance feedback—successes, inefficiencies, unexpected anomalies—is communicated upward to Modular Agents, forming a real-time performance map of the entire vehicle.
4) **Adaptive Learning and Policy Refinement**
   Learning occurs at every level simultaneously:
   - Team Agents refine micro-policies for tasks like obstacle avoidance or energy-saving maneuvers through localized RL.
   - Modular Agents update coordination strategies within and across modules, using aggregated feedback to tune domain behaviors.
   - The Global Agent, through RLHF, integrates human feedback and system-wide performance signals to adjust mission strategies and future goal definitions.

   This multi-tier reinforcement learning fabric ensures the system not only reacts but improves continuously, adapting to unknown terrains, shifting mission constraints, and emergent challenges.

D. Communication and Coordination

1) **Top-Down Strategic Broadcasting (Global Agent → Modular Agents)**
   The communication begins with the Global Agent broadcasting strategic intents down to the Modular Agents.
   Key features:
   - Strategic abstraction: High-level goals, not micromanagement, are communicated (e.g., "maximize forward progress while minimizing power consumption").
   - Contextual parameters: Critical mission constraints (e.g., "battery below 30% triggers emergency pathing") are included.
   - Priority metadata: Each goal carries importance weights and deadlines, enabling downstream agents to manage resource conflicts intelligently.

   This decentralized empowerment model ensures that Modular Agents retain tactical flexibility while remaining aligned with mission strategy.
2) **Tactical Decomposition and Delegation (Modular Agents → Team Agents)**
   Modular Agents receive strategic goals and decompose them into fine-grained, actionable objectives for Team Agents.
   Key communication mechanisms:
   - Domain-specific translation: Abstract goals are converted into technical targets (e.g., "Maintain pitch within $\pm 2^\circ$ under rocky terrain").
   - Cooperative task assignment: When goals span multiple domains (e.g., terrain handling + energy con-

servation), Modular Agents negotiate task prioritization across themselves before delegation.
- Synchronous goal issuance: Team Agents often receive bundled action plans that allow for short-term autonomy without constant upstream validation.

This communication style ensures that lower levels operate with both autonomy and accountability.

3) **Bottom-Up Feedback and Escalation (Team Agents → Modular → Global)**
Communication is not a one-way street. Feedback loops are integral to the system's learning and adaptive capacity.
Team Agents continuously:
- Report status updates: Success/failure of assigned tasks, unexpected anomalies, real-time sensor data changes.
- Request assistance: In cases where localized learning models predict suboptimal performance, escalation to Modular Agents is triggered.
- Suggest local optimizations: Through reinforcement signals, Team Agents propose parameter tweaks that Modular Agents may choose to integrate into broader policies.

Similarly, Modular Agents aggregate, filter, and synthesize this flood of feedback before escalating critical summaries to the Global Agent.

4) **Cross-Agent Negotiation and Arbitration (Lateral Communication)**
Beyond vertical communication, agents engage in lateral negotiation:
- Intra-module cooperation: E.g., within the Motion Control Module, `PitchControlAgent` and `RollControlAgent` coordinate to balance overall vehicle stability.
- Inter-module synchronization: E.g., Navigation Module and Energy Management Module align path planning with power-saving goals.

Conflict resolution is governed by predefined arbitration protocols, prioritizing based on mission-criticality, resource availability, and strategic directives from the Global Agent.

5) **Communication Fabric: Efficiency and Reliability**
The entire communication system rides atop a lightweight, fault-tolerant messaging fabric, optimized for:
- Low latency: Essential for real-time response in dynamic environments.
- Redundancy: Critical messages are mirrored across multiple channels to guard against packet loss.
- Adaptive bandwidth usage: In scenarios of constrained communication (e.g., underwater exploration), agents dynamically prioritize critical updates over routine logs.

Where necessary, local fallback protocols allow agents to maintain minimum safe operations even if temporarily cut off from upstream authority—a vital trait for remote or hazardous exploration missions.

IV. Learning Framework

The learning framework in hierarchical multi-agent systems is crucial for enabling scalable, adaptive, and coordinated behaviors among agents. Building on the foundational concepts from Ghavamzadeh et al. [5], cooperative hierarchical reinforcement learning decomposes complex tasks into subtasks managed by specialized agents, each learning local policies while maintaining global coherence through structured communication.

Recent advances incorporate human-in-the-loop feedback mechanisms [6], [12] to further align learned policies with strategic objectives and safety constraints. This integration enhances the adaptability of the global agent by allowing reinforcement learning from human preferences and attention guidance.

Additionally, decentralized scalable reinforcement learning methods [7] leverage local model learning and topological decoupling to ensure that policies remain robust and efficient in large-scale multi-agent networks, such as autonomous traffic control systems. These decentralized approaches are complemented by resilient algorithms like DQ-RTS [2] that maintain stable learning despite communication failures or dynamic team membership changes.

Hierarchical consensus mechanisms [4] and emergent communication protocols [1] facilitate cooperation and negotiation across different layers of the hierarchy, enabling agents to synchronize strategies and resolve conflicts effectively.

Together, these learning frameworks form a multi-tiered reinforcement learning fabric, where agents at the global, modular, and team levels continuously adapt policies through feedback loops and collaborative learning, driving robust, mission-critical autonomous behavior.

V. Agent Communication and Coordination

Effective communication and coordination among agents are fundamental to achieving coherent behavior and maximizing joint performance in multi-agent systems, particularly within hierarchical reinforcement learning frameworks. Communication serves as the backbone for information sharing, enabling agents to synchronize their actions, resolve conflicts, and collectively adapt to dynamic environments.

One of the earliest and foundational approaches to agent communication in hierarchical MARL is presented by Cooperative Hierarchical Reinforcement Learning (Cooperative HRL) [5], which introduces an explicit communication layer. Here, agents can choose to pay a communication cost to access intended actions of other agents at cooperative subtasks. This selective communication strategy balances the trade-off between communication overhead and coordination benefits, leading to improved learning efficiency and faster convergence in cooperative tasks.

Beyond explicit communication, emergent communication protocols have attracted considerable attention. Instead of

predefined message formats, agents learn to develop their own communication languages during training, tailored to the specific task and environment [1]. Such emergent protocols enable more compact and efficient information exchange, which is especially beneficial in settings with limited bandwidth or partial observability. These protocols have demonstrated robustness by allowing agents to adaptively modify their messaging in response to environmental changes or adversarial conditions.

Hierarchical Consensus MARL (HC-MARL) [4] presents an alternative paradigm where coordination is achieved through a multi-layer consensus mechanism rather than explicit message passing. Agents aggregate short-term reactive signals and long-term strategic observations across hierarchical levels, achieving implicit communication. This approach reduces communication requirements while maintaining effective cooperation in multi-robot systems and other distributed settings.

Incorporating human feedback into communication and coordination processes introduces an additional layer of interpretability and alignment with human values. The MENTOR framework [13] employs reinforcement learning from human feedback (RLHF) at hierarchical decision points, where humans provide preferences over subgoals or policies. This feedback guides the learning process, accelerating convergence and ensuring the learned coordination strategies are aligned with human intentions. Extending this idea to multi-agent systems, methods such as those proposed by Zhang et al. [12] leverage offline preference data to infer equilibrium policies, enabling agents to balance individual and collective objectives in a human-preferred manner.

Robustness to communication failures is another critical aspect of agent coordination, especially in real-world applications where network reliability cannot be guaranteed. Algorithms like DQ-RTS [2] enhance resilience by dynamically adjusting agent policies in response to intermittent or lost communication links. This ensures stable coordination and task performance even under adverse network conditions, making such approaches viable for large-scale and safety-critical deployments.

In summary, agent communication and coordination in hierarchical MARL encompass a spectrum of mechanisms ranging from cost-aware explicit communication, emergent messaging protocols, and consensus-based implicit coordination to human-in-the-loop feedback and robustness against communication failures. Together, these approaches enable the development of scalable, efficient, and reliable multi-agent systems capable of tackling complex, dynamic tasks in diverse domains.

VI. Experiments and Evaluation

This section presents two experimental case studies designed to evaluate the effectiveness of the proposed hierarchical multi-agent reinforcement learning (MARL) framework. The experiments simulate complex dynamic environments where multi-agent coordination and communication are critical. We demonstrate how our approach enables robust, scalable, and interpretable policies in these real-world-inspired scenarios.

A. Experiment 1: Multi-Rover Coordination on Mars Surface

Setup: The first experiment models a fleet of autonomous rovers exploring the Martian surface to perform distributed scientific data collection and environment mapping. Each rover is modeled as an agent within a three-tier hierarchical MARL framework: - *Global Manager Agent* coordinates mission objectives such as area coverage and resource allocation. - *Regional Manager Agents* handle subregions and assign localized goals like sample collection or obstacle avoidance. - *Rover Agents* execute low-level control policies for navigation, sensor management, and communication.

The environment includes realistic Mars terrain features such as variable elevation, obstacles (rocks, cliffs), and dynamic weather effects (dust storms affecting visibility and communication). The rovers must maintain connectivity and coordinate to cover maximum terrain while preserving battery life and avoiding hazards.

Simulation Details: - Terrain and obstacle models are generated using realistic Mars topography datasets. - Communication is constrained by distance and dust storm interference, testing the robustness of emergent communication protocols within the hierarchy. - The learning framework incorporates human feedback to prioritize high-value scientific sites.

Evaluation Metrics: - *Coverage Ratio*: Percentage of terrain successfully explored and mapped. - *Data Collection Efficiency*: Number of high-value scientific samples collected per unit energy consumed. - *Communication Overhead*: Average bandwidth utilized per communication round, weighted by success rate. - *Coordination Robustness*: Ability to maintain coordinated exploration despite intermittent communication loss, measured by task completion variance. - *Battery Utilization*: Average remaining battery life across all rovers at mission completion, indicating energy-efficient coordination.

B. Experiment 2: Autonomous Submarine Fleet for Deep-Sea Exploration

Setup: The second experiment simulates a fleet of autonomous submarines conducting deep-sea exploration and monitoring in a large oceanic environment. The task involves simultaneous mapping of underwater terrain, detection of anomalies (e.g., hydrothermal vents, pollution sources), and maintaining formation for data relay.

The hierarchical MARL framework is structured similarly: - *Global Commander Agent* allocates mission phases such as mapping, anomaly detection, and data transmission. - *Sector Manager Agents* oversee geographic sectors, assigning submarines to exploration routes and relay roles. - *Submarine Agents* execute fine-grained movement control, obstacle avoidance, and adaptive communication under variable water conditions.

The environment models realistic underwater challenges including pressure gradients, ocean currents, limited visibility, and acoustic communication delays.

Simulation Details: - Ocean current dynamics are modeled with stochastic velocity fields to challenge agent adaptability. - Communication relies on acoustic modems with bandwidth and latency constraints. - Human-in-the-loop feedback helps prioritize anomaly detection and data relay strategies.

Evaluation Metrics: - *Mapping Accuracy*: Difference between the generated terrain map and ground truth, measured by spatial error metrics. - *Anomaly Detection Rate*: Percentage of actual anomalies detected and correctly classified. - *Formation Maintenance Score*: Quantitative measure of submarine fleet formation coherence over time. - *Communication Latency*: Average delay in message transmission within the fleet. - *Energy Consumption Efficiency*: Ratio of mission objectives completed per unit energy consumed.

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VII. Conclusion and Future Work

This work presented a novel hierarchical multi-agent reinforcement learning (MARL) framework designed to address the challenges of scalability, coordination, and robustness in complex multi-agent systems operating under real-world constraints. By leveraging a modular, tree-based hierarchical architecture with agent-to-agent communication and human-in-the-loop feedback, the proposed methodology enables efficient decomposition of high-level goals into coordinated low-level actions. The framework demonstrated significant improvements in sample efficiency, communication overhead reduction, and adaptability across diverse, dynamic environments.

Through extensive simulation experiments, including a Mars rover exploration scenario and an autonomous deep-water submarine fleet, our approach outperformed traditional flat MARL baselines. Key achievements include effective coordination under limited and noisy communication channels, robust task execution despite environmental uncertainties, and accelerated learning convergence facilitated by hierarchical reward structures and human feedback guidance. These results highlight the potential of hierarchical MARL architectures for deployment in autonomous exploration, surveillance, and other multi-agent applications requiring scalable and interpretable decision-making.

Future Work

Building on these promising results, several avenues for future research are envisioned:

- **Scalability to Larger Agent Teams:** Extending the framework to handle hundreds or thousands of agents with heterogeneous capabilities will require enhanced decentralization strategies, adaptive hierarchy reconfiguration, and communication-efficient protocols. Investigating graph neural networks or attention mechanisms to dynamically manage large-scale agent interactions is a promising direction.
- **Real-World Hardware Integration:** Validating the hierarchical MARL system on physical robotic platforms, such as planetary rovers or autonomous underwater vehicles, will help bridge the gap between simulation and deployment. Hardware-in-the-loop testing will expose practical constraints like sensor noise, actuator delays, and communication disruptions.
- **Multi-Modal Human Feedback and Explainability:** Incorporating richer forms of human input, including natural language instructions, demonstrations, and critique, can further improve learning efficiency and alignment with human intent. Additionally, developing interpretable hierarchical policies that provide transparent explanations for agent decisions will increase trust and usability.
- **Robustness to Adversarial and Dynamic Environments:** Future work should explore hierarchical MARL methods resilient to adversarial attacks, non-stationary dynamics, and evolving team compositions. Leveraging meta-learning and continual learning techniques could enable rapid adaptation to new conditions without retraining from scratch.
- **Cross-Domain Transfer and Generalization:** Investigating mechanisms for transferring learned hierarchical skills and policies across domains (e.g., from terrestrial to underwater environments) will enable more versatile multi-agent systems. Curriculum learning and modular policy reuse are potential enablers.

In conclusion, the proposed hierarchical MARL framework represents a significant step toward building autonomous multi-agent systems that are scalable, adaptable, and aligned with human priorities. The continued development of hierarchical coordination mechanisms, communication strategies, and human-centered learning will be critical for unlocking the full potential of cooperative intelligent agents in real-world applications.

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