A Reliable Heterogeneous Multi-Robot Coordination Framework for Dynamic Task Assignment

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***Abstract*—Decentralized Heterogeneous Multi-Robot Systems (HMRS) require robust coordination strategies to operate effectively in dynamic environments. However, high-stakes HMRS missions require seamless coordination among the robotic agents to mitigate the operational stagnation typical of centralized architectures. This framework proposes a prioritized next-best-agent hierarchy that leverages Multi-Criteria Decision-Making (MCDM) approaches for adaptive task allocation. The framework uses an asynchronous event-driven architecture to enable scalable, stateless communication among the robots by adopting a robot ecology perspective, allowing autonomous role transitions triggered by Q-value threshold conditions generated via a modified-VIKOR formula.**

***Index Terms*—Decentralized Heterogeneous Multi-Robot Systems, Dynamic Task Allocation, Multi-Criteria Decision Making, Asynchronous Event Bus, Robot Ecology, Modified- VIKOR.**

I. Introduction

MULTI-ROBOT Systems (MRS), composed of two or more robots working collaboratively to accomplish specific tasks, have emerged as a transformative technology [1] in high-stakes dynamic environments such as Search and Rescue (SAR). The Heterogeneous Multi-Robot System (HMRS) deployment in time-critical domains (like SAR operations) demands a fundamental shift in how missions are structured. Traditionally, task prioritization and team formation in MRS have been treated as distinct individual aspects of task planning, as prioritization determines what is important and team formation determines who is available. However, this disintegrated approach often results in sub-optimal allocation where the assigned team's capabilities do not align with the prioritized mission goals. A unified framework that merges both aspects can ensure that the prioritization logic aligns directly with the team formation process.

Despite the challenges in the task planning phase, task execution is often hindered by communication overhead and operational stagnation in synchronous, centralized MRS. In traditional centralized HMRS architectures, the task orchestrator requires constant updates of the global states to maintain synchronization across the fleet. It saturates the network with repetitive polling data. More critically, if a single robot suffers a hardware failure or enters a no-signal, dead zone, the entire fleet often pauses and waits for the next update from the central server to re-synchronize the mission state. This operational stagnation is one of the main bottlenecks that prevent the effective deployment of HMRS in a dynamic, high-stakes environment. In this paper, we propose an Asynchronous Heterogeneous Task Orchestration via a modified-VIKor (AHTOVIK) framework to overcome these synchronization bottlenecks through an asynchronous event-driven architecture, shifting the focus from server-push models to an end-pull architecture. AHTOVIK proposes a novel unified algorithm for task prioritization and team formation in HMRS, leveraging different Multi-Criteria Decision-Making (MCDM) methodologies through context-aware criteria selection. Once tasks are assigned to designated robot teams based on task priorities and robot capabilities, the AHTOVIK framework utilizes an Asynchronous Event Bus (AEB) to facilitate a stateless communication medium. Finally, the framework achieves decentralization by realizing the concept of Robot Ecology [2]. AHTOVIK views the HMRS as a self-healing ecosystem that allows reflexive resiliency at the edge.

II. AHTOVIK Framework

AHTOVIK is a reliable decentralized coordination framework for dynamic task assignment, emphasizing the transition from the traditional static assignment to dynamic, context-aware, team synthesis. Our algorithm is conceptualized as a four-block pipeline that will translate the environmental uncertainty into a stable, heterogeneous team configuration through an asynchronous, event-driven backbone, as shown in Figure 1.

The AHTOVIK framework utilizes a distributed logic model where the computational burden is shifted to the individual robots, ensuring reflexive autonomy at the edge. It operates

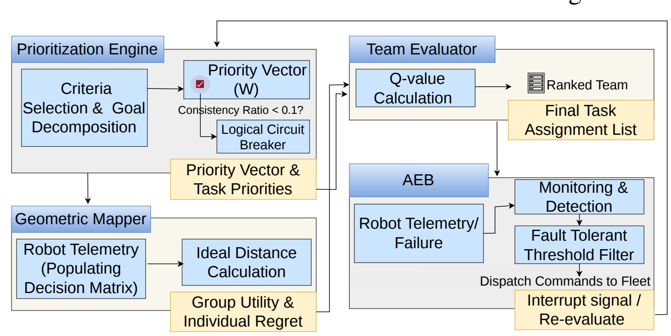

Fig. 1: AHTOVIK Framework Architecture

by processing hierarchical goals into a verified priority vector, which is then mapped against real-time robot telemetry. The framework is designed as a middleware between the raw hardware and high-level service orchestration, where the initial task demands are processed through a compromise index (Q) to form a ranked heterogeneous team using a modified-VIKOR algorithm see Section III). This Q-value serves as a metric for prioritized next-best agent hierarchy and effectively organizes the heterogeneous fleet into ecological niches based on their immediate suitability for a specified task. Unlike traditional models, AHToVIK treats coordination as a closed-loop system through the AEB. The AEB continuously monitors the fleet, triggering re-evaluation cycles if a fault-tolerant threshold is breached, thereby ensuring mission continuity without a centralized bottleneck.

III. Core Components

1) Task Prioritization Engine: The Prioritization Engine initiates the orchestration by performing context-aware criteria selection and hierarchical goal decomposition. It utilizes a pairwise comparison matrix (M) to derive the verified priority vector (W). To ensure logical integrity, a consistency ratio check is performed where the logical circuit breaker is triggered if the ratio exceeds 0.1, preventing flawed task priorities from reaching the mapping stage.

2) Geometric Mapping and Team Evaluation: The geometric mapper populates the decision matrix using the live robot telemetry, normalizing data to perform ideal distance calculations. One of the major contributions of this block is the use of Euclidean norm to identify the ideal best (D_i^+) and worst case (D_i^-) scenarios through mathematical anchoring. These values are passed to the team evaluator, which fuses task demands with group utility and individual regret. One of the core contributions of the paper lies here, as the compromise index (Q) calculation uses a modified-VIKOR formula (see Formula 1 below). This calculation ranks the robots based on their overall fitness for a specific task, resulting in a heterogeneous team, where the roles are assigned deterministically. The robot with $Q_{\min}$ becomes a member of the primary niche, and the successors are kept in the standby queue. This ranking is mirrored across all the robots, allowing the HMRS to have a shared source of truth without the use of a centralized server, letting the AEB remain stateless.

$$Q = v\left(\frac{D_i^+ - D_i\min^+}{\Delta D_i^+}\right) + (1-v)\left(\frac{D_i\max^- - D_i^-}{\Delta D_i -}\right) \quad (1)$$

3) AEB as an Operational Ecosystem: (i) AEB as a digital Habitat : In AHToVIK, the AEB acts as the atmosphere where the fitness scores (Q-values) are exhaled by robots as discrete events, maintaining the AEB stateless. It does not make decisions or store a central cache, as the decisions emerge from how the robots sense the environment. The transition from the team evaluator to the AEB marks the shift from planning to execution. This phase is characterized by its end-pull logic, where the mission states are maintained through local reflexes rather than top-down commands. *(ii) Niches in AEB :* In AHToVIK, a niche is defined as a mathematical and functional space occupied by each robot determined by its compromise index. The robot with the primary niche will actively execute the task, and robots with higher Q-values will be in stand-by niches to support the primary member. Niches are implemented by a selective publish-subscribe methodology, and the AEB monitors the health of these niches in real-time. If any active robot's Q-value breaches the 10 percent threshold (i.e., if any change in the active robot or its environment occurs that has more than 10 percent fluctuations to the current state), it signifies a Niche breach.

IV. Case Study: Earthquake Search and Rescue

Following a major earthquake, an HMRS consisting of Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), and tracked creeper robots is deployed to assess structural damage and locate trapped survivors. Multiple mission objectives are generated simultaneously, including victim detection, debris inspection, medical supply delivery, and structural monitoring. AHToVIK first determines the relative urgency of these tasks according to the operational objectives and forms task-specific teams. For example, a UAV may be selected for rapid victim localization, a UGV for navigating open debris fields, and a creeper robot for entering confined spaces beneath collapsed structures. During execution, suppose the active UGV assigned to debris inspection becomes immobilized after encountering unstable rubble. Instead of waiting for a centralized coordinator to recompute the global allocation, the AEB propagates the failure event, while each robot already possesses the same ranked next-best-agent hierarchy. The highest-ranked standby UGV autonomously promotes itself to the active role based on its Q-value, preserving mission continuity. The implementation and validation results are available in the replication package[1].

V. Conclusion

The AHToVIK framework presented in this paper provides a robust and comprehensive framework for evaluating and ranking robots according to their capabilities. The AHToVIK framework depicts a shift from fragile centralized multi-robot task-allocation to a resilient robot ecology. By integrating the high-fidelity MCDM ranking with a stateless asynchronous execution model, the framework achieves a reflexive autonomy essential for high-stakes dynamic environments. The modified compromise index ensures that tasks are assigned not just to the best candidate but also to the robot that offers the best compromise among all evaluation aspects.

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