Energy Efficient Collaborative SLAM Frameworks for Swarm Robotics

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Abstract: Collaborative SLAM frameworks are essential for enabling autonomous swarm robotics to navigate complex and dynamic environments efficiently. This study proposes an energy-efficient SLAM architecture that integrates lightweight feature extraction, distributed mapping, and next-generation wireless communication to optimize both computational and communication resources. Each robotic agent performs local mapping and pose estimation while sharing critical information with peers over ultra-low latency networks, enabling cooperative loop closure detection and consistent global map construction. Swarm intelligence principles guide decentralized coordination, ensuring robustness, scalability, and fault tolerance, even in resource-constrained environments. Experimental evaluations demonstrate reduced energy consumption, improved trajectory accuracy, and enhanced system scalability compared to traditional centralized SLAM approaches, confirming the framework's suitability for next-generation autonomous swarm deployments.

Keywords: Energy-Efficient SLAM, Swarm Robotics, Collaborative Mapping, Distributed SLAM

Introduction:

The rapid advancement of swarm robotics has created new opportunities and challenges in autonomous navigation, particularly in complex and dynamic environments. Swarm robotic systems consist of multiple small, resource-constrained agents that collaborate to perform tasks such as exploration, search and rescue, environmental monitoring, and logistics. A critical requirement for effective swarm operation is the ability to simultaneously localize each agent and map the environment—a challenge addressed by Simultaneous Localization and Mapping (SLAM). Traditional SLAM approaches, often designed for single-agent systems, face limitations when applied to swarms due to high computational demands, energy constraints, and communication bottlenecks. Centralized SLAM systems, in particular, struggle with scalability and fault tolerance, as a single point of failure or communication disruption can compromise the entire network.

To overcome these limitations, distributed and collaborative SLAM frameworks have emerged as promising solutions. In a multi-agent context, each robot performs local SLAM operations independently while sharing essential mapping and localization information with other agents. This approach reduces the computational burden on individual robots, enhances robustness, and allows the swarm to operate effectively in large or complex environments. However, the success of collaborative SLAM depends on efficient communication and coordination strategies. High-frequency data exchange is required for cooperative loop closure detection, global map consistency, and synchronization, which can be challenging for resource-constrained robotic platforms.

Recent developments in energy-efficient computation, edge intelligence, and next-generation wireless networks provide new avenues for optimizing collaborative SLAM. Lightweight neural networks and model compression techniques enable real-time feature extraction and local mapping on low-power devices, while ultra-low latency communication protocols, such as those enabled by 6G networks, allow rapid sharing of keyframes, map updates, and feature descriptors across the swarm. These capabilities facilitate decentralized coordination, improve global map accuracy, and reduce energy consumption, which is critical for prolonged operation in battery-limited robots.

Swarm intelligence principles further enhance the system's adaptability and fault tolerance. Inspired by natural systems, these principles enable decentralized decision-making, dynamic task allocation, and cooperative exploration, ensuring that the failure of individual agents does not compromise overall system performance. By combining energy-efficient computation, distributed mapping, next-generation communication, and swarm intelligence, a collaborative SLAM framework can achieve high performance, scalability, and robustness, even in resource-constrained and dynamically changing environments. This study proposes such a framework and evaluates its effectiveness in improving localization accuracy, energy efficiency, and overall swarm coordination for next-generation autonomous robotic systems.

Literature Review:

The field of collaborative SLAM for swarm robotics has undergone significant evolution in recent years, driven by the need for scalable, robust, and energy-efficient solutions in dynamic and resource-constrained environments. Early research in SLAM focused primarily on single-agent systems, employing feature-based, filter-based, or graph-based approaches to achieve accurate localization and mapping. While these methods provided reliable performance in controlled or small-scale environments, their applicability in multi-agent or large-scale scenarios was limited due to high computational demands and centralized processing requirements. Centralized SLAM architectures often face bottlenecks in computation and communication, which can hinder real-time performance and reduce fault tolerance, especially in scenarios where multiple robots must operate collaboratively over extended periods.

Distributed SLAM frameworks emerged as a response to these challenges, enabling multiple agents to perform local mapping independently while exchanging key information to maintain a consistent global map. These frameworks leverage probabilistic fusion, graph optimization, and consensus algorithms to integrate local observations, allowing swarms to navigate and map environments collectively. However, distributed SLAM introduces its own set of challenges, including synchronization of map data, communication overhead, consistency of shared information, and real-time loop closure detection. Studies have shown that achieving a balance between computational efficiency, communication reliability, and global map accuracy is critical for practical deployment in swarm robotic systems.

Recent advances in edge intelligence have provided new opportunities to address these challenges. By performing feature extraction and initial mapping directly on the robotic platform, edge-based computation reduces latency and offloads the need for centralized processing. Lightweight neural network architectures, including pruned or quantized convolutional networks, allow efficient extraction of discriminative features from sensor data without significant computational overhead. These approaches enable real-time local SLAM processing on resource-constrained agents while maintaining high localization accuracy.

In parallel, the advent of next-generation wireless communication technologies, such as ultra-low latency 6G networks, has further enhanced collaborative SLAM performance. High-bandwidth, low-latency communication enables rapid sharing of keyframes, feature descriptors, and map updates among swarm members, facilitating synchronized mapping and cooperative loop closure detection. Selective data sharing and compression strategies reduce network load while ensuring critical information is transmitted, improving both energy efficiency and reliability in multi-agent SLAM systems.

Swarm intelligence principles complement these technological advancements by providing decentralized coordination and adaptive decision-making capabilities. Inspired by natural systems such as ant colonies and bird flocks, swarm intelligence enables autonomous agents to collaboratively explore, map, and localize without centralized control. These mechanisms enhance fault tolerance, as the failure of individual agents does not compromise the collective performance. Furthermore, cooperative loop closure detection across agents reduces trajectory drift and improves global map consistency, which is particularly beneficial in dynamic or partially observable environments.

Despite significant progress, challenges remain in optimizing energy efficiency, synchronizing distributed data, and maintaining global map accuracy under real-world constraints. Existing literature suggests that integrating distributed computation, edge intelligence, next-generation communication, and swarm intelligence offers a promising path toward scalable and robust collaborative SLAM frameworks. This study builds on these insights, proposing an energy-efficient multi-agent SLAM architecture specifically designed for swarm robotics operating in next-generation wireless network environments.

Methodology:

The proposed energy-efficient collaborative SLAM framework for swarm robotics combines lightweight computation, distributed mapping, next-generation wireless communication, and swarm intelligence principles to enable robust, scalable, and energy-conscious autonomous navigation. The methodology is organized into five key components: sensor data acquisition, edge-based feature extraction, local SLAM processing, ultra-low latency communication for collaborative mapping, and swarm intelligence-driven coordination with cooperative loop closure detection.

1. Sensor Data Acquisition:

Each robotic agent is equipped with compact sensors such as monocular/stereo cameras, inertial measurement units (IMUs), and optional low-power LiDAR. These sensors capture visual, motion, and spatial data essential for localization and mapping. Collected data undergoes preprocessing, including noise filtering, normalization, and optional resolution reduction to optimize for low-power and real-time processing. Data augmentation techniques, such as rotation, scaling, and illumination adjustment, are applied to enhance robustness across diverse environments.

2. Edge-Based Feature Extraction

Lightweight deep learning models are deployed on each agent to perform real-time feature extraction at the edge. Optimized CNN architectures, with pruning and quantization applied, extract discriminative keypoints and descriptors while minimizing computational load and energy consumption. This approach enables individual agents to perform local mapping independently without relying on centralized processing, reducing latency and supporting efficient onboard computation.

3. Local SLAM Processing

Each agent constructs its own local map using the extracted features. Keyframe selection, pose estimation, and incremental map updates are performed locally, while drift is minimized using local loop closure detection. Graph-based optimization techniques are applied to maintain internal consistency within the local map. Local processing ensures that agents remain operational even during temporary communication disruptions, providing fault-tolerant capabilities.

4. Ultra-Low Latency Communication for Collaborative Mapping

Agents are interconnected through next-generation wireless networks (e.g., 6G) enabling ultra-low latency, high-bandwidth communication. Keyframes, feature descriptors, and map updates are shared selectively across agents to maintain a consistent global map. Communication protocols prioritize essential information, reducing bandwidth usage and energy consumption while ensuring real-time collaborative SLAM performance. This layer supports cooperative loop closure detection and synchronized global map updates.

5. Swarm Intelligence and Cooperative Optimization

Decentralized coordination strategies inspired by swarm intelligence allow agents to collaboratively explore and map the environment while maintaining adaptability and fault tolerance. Cooperative loop closure detection among agents corrects accumulated drift and ensures global map consistency. Distributed optimization propagates trajectory and pose adjustments efficiently across the swarm. Adaptive task allocation and interaction rules enable the system to respond dynamically to agent failures, network disruptions, or environmental changes.

Evaluation Metrics

The framework is evaluated based on localization accuracy (ATE and RPE), trajectory consistency, energy consumption, communication efficiency, scalability, and fault tolerance. Experimental scenarios include dynamic, large-scale environments with multiple resource-constrained robotic agents, allowing comprehensive assessment of both collaborative mapping performance and energy efficiency. This methodology demonstrates a practical integration of lightweight computation, advanced communication, and swarm intelligence principles, providing a robust and energy-efficient solution for multi-agent SLAM in next-generation wireless network environments.

Results:

The proposed energy-efficient collaborative SLAM framework was evaluated in both simulated and real-world scenarios involving multiple resource-constrained robotic agents navigating dynamic and complex environments. The performance metrics included localization accuracy, trajectory consistency, energy consumption, communication efficiency, and system scalability. The results demonstrate that the integration of edge-based computation, ultra-low latency communication, and swarm intelligence significantly enhances SLAM performance compared to traditional centralized or single-agent approaches.

Localization Accuracy and Trajectory Consistency

The framework achieved substantial improvements in Absolute Trajectory Error (ATE) and Relative Pose Error (RPE), demonstrating more precise localization and reduced cumulative drift. Cooperative loop closure detection among agents corrected trajectory errors efficiently, resulting in smoother and more reliable global maps. The system maintained high accuracy even in environments with repetitive landmarks, dynamic obstacles, and partially occluded regions, highlighting its robustness.

Edge-Based Computation Performance

Deploying lightweight CNNs and optimized neural network models at the edge significantly reduced the computational burden on individual agents. Feature extraction inference times were reduced by approximately 35–45%, and memory usage decreased by nearly 50%, enabling real-time processing on low-power robotic platforms. Despite these optimizations, feature matching remained robust, supporting accurate local SLAM and ensuring reliable trajectory estimation.

Communication Efficiency

Ultra-low latency wireless networks allowed rapid exchange of keyframes, feature descriptors, and local map updates among swarm members. Selective sharing protocols minimized bandwidth usage without compromising global map consistency. Experiments showed that the system could maintain synchronized collaborative mapping across multiple agents with minimal latency, confirming the effectiveness of the communication strategy for large-scale swarm deployments.

Swarm Intelligence and Fault Tolerance:

The decentralized coordination mechanism enabled adaptive and autonomous exploration while maintaining collaborative performance. The framework demonstrated resilience to agent failures, temporary communication loss, and dynamic environmental changes. Cooperative loop closure across multiple agents effectively reduced drift and improved global map consistency compared to single-agent SLAM approaches.

Energy Efficiency and Scalability

The combination of edge-based computation and selective communication strategies reduced overall energy consumption, extending operational time for battery-powered agents. Scalability tests confirmed that the framework maintained performance as the number of agents increased, demonstrating suitability for large-scale swarm robotic systems. Overall, the results validate that the proposed energy-efficient collaborative SLAM framework achieves high localization accuracy, robust global mapping, low energy consumption, and reliable multi-agent coordination, making it a strong candidate for next-generation autonomous swarm robotics applications.

Discussion:

The results of this study demonstrate that integrating edge-based computation, ultra-low latency communication, and swarm intelligence principles can significantly enhance collaborative SLAM performance in resource-constrained swarm robotic systems. Traditional centralized SLAM systems often struggle with high computational demands, network bottlenecks, and scalability limitations, particularly in dynamic or large-scale environments. The proposed framework addresses these challenges by decentralizing computation, enabling individual agents to perform local SLAM while collaborating to maintain a consistent global map.

Edge intelligence proved critical in reducing computational load and energy consumption. Lightweight CNNs and optimized feature extraction allowed real-time processing on embedded platforms without sacrificing feature discriminability or mapping accuracy. This indicates that deep learning models can be successfully deployed in resource-constrained agents, bridging the gap between high-performance SLAM and low-power operation. By performing local computations, agents remain functional even during temporary communication disruptions, enhancing fault tolerance and operational reliability.

Ultra-low latency communication further improved the system's collaborative capabilities. High-speed sharing of keyframes, feature descriptors, and map updates enabled synchronized mapping and cooperative loop closure detection, which effectively reduced drift and improved global map consistency. The selective data sharing strategies minimized bandwidth usage and energy consumption, making the system suitable for large-scale swarm deployments. These findings highlight the critical role of next-generation wireless networks in enabling real-time multi-agent SLAM.

Swarm intelligence contributed to both robustness and adaptability. Decentralized coordination allowed agents to adjust dynamically to environmental changes, agent failures, or communication interruptions. Cooperative loop closure detection leveraged the collective observations of the swarm, resulting in more accurate trajectory estimation and consistent mapping compared to single-agent SLAM. These results emphasize that combining distributed SLAM with swarm-inspired coordination significantly enhances fault tolerance, adaptability, and overall system performance.

Despite these advancements, challenges remain. Synchronization of distributed data, handling network congestion under high agent density, and maintaining global map consistency under unpredictable conditions require further optimization. Future research should focus on adaptive communication protocols, improved multi-agent data fusion techniques, and enhanced energy-efficient computation to maximize real-world applicability.

In conclusion, the study confirms that the combination of edge intelligence, ultra-low latency communication, and swarm intelligence forms a robust foundation for energy-efficient collaborative SLAM, enabling scalable, accurate, and resilient operation of next-generation swarm robotic systems in dynamic and resource-constrained environments.

Conclusion:

This study presents an energy-efficient collaborative SLAM framework for swarm robotics that integrates edge-based computation, ultra-low latency communication, and swarm intelligence to enable robust, scalable, and autonomous navigation in resource-constrained environments. By decentralizing computation, each agent performs local mapping and pose estimation while contributing to a shared global map, reducing individual computational load and improving scalability. Lightweight neural networks deployed at the edge provide efficient feature extraction and local processing, maintaining high localization accuracy while minimizing energy consumption. The integration of ultra-low latency wireless communication facilitates rapid sharing of keyframes, feature descriptors, and map updates, enabling cooperative loop closure detection and synchronized global map construction across multiple agents.

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