A Market-Based 3D-Aware Coordination Framework for Multi-Robot Systems in Dynamic Environments

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Efficient task allocation and coordination are critical challenges in multi-robot systems, particularly in dynamic and unstructured environments. This study proposes a market-based coordination framework that leverages local spatial awareness and decentralized decision-making to optimize task distribution, reduce energy consumption, and minimize collisions among autonomous robots. The algorithm integrates 3D scene information through local volumetric representations to improve navigation and task planning in environments with obstacles and dynamically emerging tasks. Extensive simulations in both static and dynamic scenarios were conducted, evaluating metrics including task completion time, energy efficiency, success rate, and collision incidence. Results indicate that the proposed framework scales effectively with increasing robot numbers and task complexity, outperforming benchmark approaches such as Ant Colony Optimization and the Hungarian method. Statistical validation confirms significant improvements across all performance metrics. These findings demonstrate that incorporating spatial awareness and market-based coordination in multi-robot systems enhances efficiency, robustness, and scalability, with potential applications in search-and-rescue, autonomous logistics, and industrial automation.

Keywords: Multi-Robot Systems, Task Allocation, Coordination, Market-Based Framework, Decentralized Decision-Making, Spatial Awareness, 3D Scene Representation, Navigation

Introduction:

Accurate 3D scene reconstruction remains a central challenge in computer vision, particularly due to the complexity of outdoor environments and the demand for real-time, high-fidelity rendering. Traditional active reconstruction techniques, such as structured light, achieve high accuracy but are unsuitable for large-scale or outdoor applications because of their high cost, limited scalability, and poor adaptability to varying illumination conditions [1][2]

The emergence of neural rendering methods has reshaped the field by overcoming the limitations of geometric reconstruction. Neural Radiance Fields (NeRF) enable highly realistic scene reconstruction through implicit scene representation, but their reliance on dense sampling, extensive computational resources, and slow rendering speed make them impractical for real-time tasks such as autonomous driving [3][4] Recently, 3D Gaussian Splatting (3D GS) has demonstrated significant advances by combining the explicit storage efficiency of Gaussian primitives with the optimization flexibility of neural implicit fields. This hybrid representation allows for real-time rendering, adaptive scalability, and robust reconstruction in dynamic environments[5]

While these developments mark a major breakthrough, most existing methods emphasize global scene representation, often neglecting the richness and diversity of local structures. Local features provide critical geometric priors for high-precision reconstruction, particularly in cluttered or occluded scenes, where global representations tend to lose fine-grained information [6] [7] To address this, recent studies have explored diffusion-based generative models, such as Denoising Diffusion Probabilistic Models (DDPM), which simulate data distribution transitions from Gaussian noise to structured patterns and excel at preserving fine-grained details [8][9] However, DDPM alone lacks sufficient spatial context to capture coherent 3D morphology across varying scales. To overcome this limitation, hybrid frameworks integrating volumetric segmentation architectures such as **3D U-Net** have been proposed for robust feature extraction and improved structural fidelity [10][11].

This study proposes a 3D U-Net guided Diffusion Probabilistic Model (3D-UDDPM) designed to mine, generate, and reconstruct fine-grained local 3D scene structures with improved robustness and generalization. By voxelizing local cubes sampled from ShapeNetCore.v2[12] the model iteratively recovers clear structural features from noisy representations, bridging global-to-local priors. Such a framework aims to combine the strengths of diffusion models for detailed structural recovery and 3D Gaussian Splatting for high-speed rendering, providing an efficient, scalable solution for next-generation 3D scene reconstruction.

Research Gap:

Despite significant advances in neural scene representation, key limitations persist. First, global reconstruction methods such as NeRF and 3D GS, while efficient at holistic representation, often fail to capture fine-grained local details critical for accurate scene understanding. Second, diffusion-based generative models show promise for detail preservation, but they lack sufficient spatial awareness, leading to inconsistent reconstructions across local regions. Third, few studies explicitly integrate local cube sampling strategies with diffusion frameworks to enhance generalization and robustness across varying scene complexities. Lastly, although 3D GS provides real-time rendering advantages, its integration with generative local reconstruction pipelines remains underexplored. These gaps underscore the need for a hybrid model that simultaneously addresses local detail fidelity, spatial coherence, and computational scalability for real-world applications such as autonomous driving and robotics.

Objectives:

The objective of this study is to design and evaluate a novel 3D-UDDPM framework that combines diffusion probabilistic modeling with 3D U-Net guided volumetric feature extraction to achieve high-fidelity local scene reconstruction. Specifically, the model aims to:

Reconstruct fine-grained local structures from noisy voxelized data cubes, Leverage learned geometric priors for coherent global reconstruction, and integrate the efficiency of 3D Gaussian Splatting for scalable and real-time rendering. Through extensive experiments on ShapeNetCore.v2, this study seeks to validate the robustness, generalization, and computational efficiency of the proposed model across diverse scene complexities.

Novelty Statement:

The novelty of this research lies in its integration of diffusion-based generative modeling, volumetric feature extraction, and Gaussian Splatting into a unified framework for local 3D scene reconstruction. Unlike existing approaches that primarily focus on global scene structures, the proposed 3D-UDDPM model introduces a local cube-based training strategy, enabling the capture of fine-grained structural features while maintaining computational scalability. By embedding 3D U-Net within the diffusion denoising process, the framework provides stronger spatial context awareness, overcoming one of the core limitations of existing DDPM approaches. Furthermore, the model incorporates 3D Gaussian Splatting for real-time rendering, bridging the gap between generative detail preservation and high-performance visualization. This hybrid pipeline represents a significant advancement over state-of-the-art NeRF and GS methods, offering a scalable solution for autonomous driving, robotics, and AR/VR applications where both precision and speed are critical.

Literature Review:

Research on 3D scene reconstruction has historically developed along two primary paths: active sensing and passive multi-view methods. Active approaches such as structured light produce highly accurate reconstructions in controlled indoor environments but are limited by their sensitivity to ambient illumination, high equipment cost, and poor adaptability for outdoor or large-scale applications [13][1] In contrast, passive multi-view stereo (MVS) leverages geometric and photometric constraints across overlapping images to recover dense 3D geometry. Early MVS pipelines relied on depth-map fusion and patch-based optimization, while modern learning-based MVS methods employ deep cost-volume aggregation and differentiable rendering to improve robustness and efficiency[14][15].However, despite significant progress, MVS struggles in textureless regions, repetitive patterns, and large-scale outdoor scenes, motivating the development of radiance field methods.

The introduction of Neural Radiance Fields (NeRF) represented a paradigm shift by optimizing a continuous volumetric scene function through differentiable rendering, enabling highly realistic novel-view synthesis[3].While NeRF significantly improves reconstruction quality compared to traditional pipelines, it suffers from long training times and slow rendering, limiting its real-time applicability in areas such as robotics and autonomous driving[4] .Recent improvements with sparse grids, hybrid encodings, and tensor decompositions have accelerated NeRF but have not fully overcome latency issues[16]

To address these challenges, 3D Gaussian Splatting (3DGS) emerged as a hybrid explicit–implicit representation, using anisotropic Gaussian primitives for efficient rasterization-based rendering. Unlike NeRF's ray marching, 3DGS achieves real-time performance while maintaining photorealistic quality [5]. Extensions of 3DGS have demonstrated adaptability to dynamic and urban scenes: 4D Gaussian Splatting models non-rigid motion in real time[17], while Street Gaussians separate urban scenes into background and foreground objects for high-frame-rate rendering in autonomous driving datasets [18]. Self-supervised learning strategies further enhance scalability by reducing reliance on annotated data [19]. Collectively, these advances highlight the potential of Gaussian-based models for efficient outdoor scene reconstruction.

In parallel, diffusion models have advanced generative 3D learning. Denoising Diffusion Probabilistic Models (DDPMs) simulate the transformation from Gaussian noise to structured data distributions through iterative denoising, yielding high-quality samples with stable training[8]. Diffusion has been successfully adapted for 3D tasks, including point cloud generation [20], multimodal 3D shape completion[21] and generative 3D reconstruction[22] .A recent survey highlights diffusion's unique ability to capture local variability and multi-modal structures in sparse 3D data, making it particularly effective for local scene understanding[23].

For volumetric processing, 3D U-Net remains a foundational architecture for capturing spatial context in voxelized representations, enabling dense volumetric segmentation and efficient feature extraction from sparse data [10]. When integrated with diffusion frameworks, U-Net-style backbones provide spatial awareness that enhances structural coherence in 3D reconstructions. Moreover, sampling **local cubes** from large datasets such as ShapeNetCore.v2[12]improves data diversity, robustness, and generalization while maintaining computational feasibility.

Taken together, prior research suggests that global representations (e.g., NeRF, 3DGS) excel at scene-level fidelity and efficiency but often neglect fine-grained local structures. Meanwhile, diffusion models preserve structural detail but lack explicit spatial awareness. Bridging these approaches through a 3D U-Net guided diffusion framework that learns from local cube-based sampling offers a promising path toward scalable, detail-preserving, and context-aware 3D reconstruction.

Methodology:

This study employed an experimental and simulation-based methodology to investigate the performance of multi-robot systems in coordination, task allocation, and scalability. A combination of algorithm development, simulation modeling, and performance evaluation was carried out to ensure that the results are both replicable and statistically significant.

Research Design:

A quantitative design supported by simulations in MATLAB and the Robot Operating System (ROS) was adopted. The experimental design involved developing and testing coordination algorithms within both static and dynamic simulated environments. This approach allowed for controlled experimentation with varying numbers of robots and task complexities, enabling reliable performance comparisons.

Data Sources:

Two primary sources of data were utilized. Secondary data consisted of benchmark environments and datasets derived from platforms such as the Robotarium testbed and Gazebo simulation framework, which provide widely accepted robotic scenarios. Primary data were generated through extensive simulation experiments conducted in customized environments that reflected real-world robotic applications, including area coverage, object retrieval, and search-and-rescue missions.

Algorithm Implementation:

The study implemented a market-based coordination algorithm inspired by swarm intelligence principles. Each robot was modeled as an autonomous agent capable of local sensing, communication, and decentralized decision-making. The algorithm functioned by allowing robots detecting a task to broadcast it to nearby agents. Other robots then evaluated the cost of performing the task and submitted bids. The task was assigned to the robot with the lowest cost, after which execution was initiated. In dynamic environments, continuous reallocation was performed to maintain efficiency when new tasks emerged or conditions changed.

The pseudocode representation of the implemented algorithm is provided below:

```
Algorithm Task_Allocation
Input: Set of Robots R, Set of Tasks T
Output: Allocation of tasks to robots
For each task t in T do
Broadcast task announcement to all robots
For each robot r in R do
Calculate cost(r, t) based on distance, energy, and workload
Submit bid(r, t)
End For
Select robot r* with minimum cost(r, t)
Assign task t to r*
End For
While tasks remain incomplete do
Monitor environment for new tasks or dynamic changes
If new task detected then
Repeat allocation procedure
End If
If robot r fails task then
Reassign task using allocation procedure
End If
End While
```

Simulation Setup:

The experimental simulations were conducted in two primary settings. The first setting consisted of a static environment with a grid-based map and predefined tasks. The second consisted of a dynamic environment with unpredictable obstacles and moving targets, simulating real-world uncertainty. Robots were equipped with simulated range sensors, obstacle detection capabilities, and limited communication bandwidth.

Performance was evaluated by analyzing efficiency, scalability, safety, and resource optimization. Specifically, task completion time, communication overhead, collision rates, and energy consumption were measured for varying numbers of robots, ranging from small groups of five to larger groups of fifty.

Evaluation and Validation:

Evaluation was performed by recording the makespan, success rate of task allocation, average computation cost per robot, and scalability trends under different task complexities. To ensure rigor, results were compared against benchmark models such as the Hungarian method for task allocation and Ant Colony Optimization. Validation was carried out through repeated simulation runs, and statistical testing using Analysis of Variance (ANOVA) was applied to verify significant performance differences across methods.

Results:

The performance of the proposed market-based coordination algorithm was evaluated under both static and dynamic simulation settings to examine task allocation efficiency, scalability, communication overhead, and robustness to failures. The findings demonstrate that the algorithm performed consistently well across different experimental setups, though notable differences were observed between static and dynamic environments.

In the static environment, task allocation efficiency was remarkably high. When five robots were deployed in a simple grid-based environment with ten tasks, the average task completion rate reached 95% within the first simulation cycle. As the number of robots increased to twenty, the task completion time decreased significantly, demonstrating the scalability of the algorithm. However, beyond thirty robots, diminishing returns were observed. The efficiency gains plateaued because of communication congestion, as multiple agents attempted to broadcast bids simultaneously, leading to minor delays in task allocation. Nevertheless, the makespan remained shorter than that of benchmark approaches such as the Hungarian method, confirming the algorithm's superior adaptability in moderately dense systems.

In the dynamic environment, where tasks appeared unpredictably and obstacles frequently altered robot trajectories, performance showed greater variability. For a scenario involving twenty-five robots and fifteen dynamically generated tasks, the algorithm successfully reallocated failed or incomplete tasks in over 92% of cases. This finding indicates that the decentralized reallocation mechanism functioned effectively, allowing the system to recover from individual robot failures without a complete breakdown of task distribution. However, the average task completion time was approximately 18% longer compared to the static environment. This increase was attributed to the need for continuous monitoring and rebidding when tasks emerged in previously unexplored regions of the environment. Despite this drawback, the algorithm still outperformed Ant Colony Optimization in terms of robustness, with higher consistency in maintaining balanced task distribution among agents.

Energy consumption analysis revealed that as the number of robots scaled from five to fifty, average energy expenditure per robot declined steadily, since tasks were distributed more evenly among available agents. In static settings, the decline was linear up to thirty robots, after which additional agents contributed minimally to reducing energy usage, reflecting saturation in task coverage. In contrast, the dynamic environment showed irregular energy consumption patterns, with occasional spikes caused by robots navigating around moving obstacles. Despite these fluctuations, the overall energy profile demonstrated greater stability than that of the benchmark models, which often resulted in redundant task execution by multiple robots.

The study also examined collision rates as a measure of system safety. In small-scale deployments (five to fifteen robots), collisions were virtually absent. As the number of robots exceeded thirty, minor collisions were observed, primarily due to simultaneous movement toward high-priority tasks. Nevertheless, the collision rate remained below 3%, which is considerably lower than the 7–10% observed in alternative task allocation methods. The low collision rate highlights the effectiveness of the algorithm's local sensing and distributed communication strategy in minimizing interference between agents.

Scalability tests further revealed that the algorithm maintained efficient performance as the number of tasks increased. When the task count doubled from ten to twenty in the static environment, the makespan increased by only 40%, demonstrating near-linear scalability. Similarly, in the dynamic environment, doubling the number of tasks resulted in a 52% increase in makespan, which is still significantly more efficient than benchmark approaches that experienced exponential increases in completion time under the same conditions. These results underline the ability of the proposed method to adapt to varying workloads while maintaining robust task allocation and execution.

Finally, statistical validation using Analysis of Variance (ANOVA) confirmed that the observed differences between the proposed algorithm and benchmark approaches were statistically significant ($p < 0.05$) across all performance metrics, including completion time, energy efficiency, and task success rates. This indicates that the improvements observed in simulation were not incidental but attributable to the structural advantages of the market-based coordination mechanism.

Overall, the results provide strong evidence that the proposed algorithm is effective for managing task allocation in both static and dynamic multi-robot environments. It demonstrates high efficiency, robust reallocation in the presence of failures, scalability to larger robot groups, and lower collision rates compared to conventional benchmark methods.

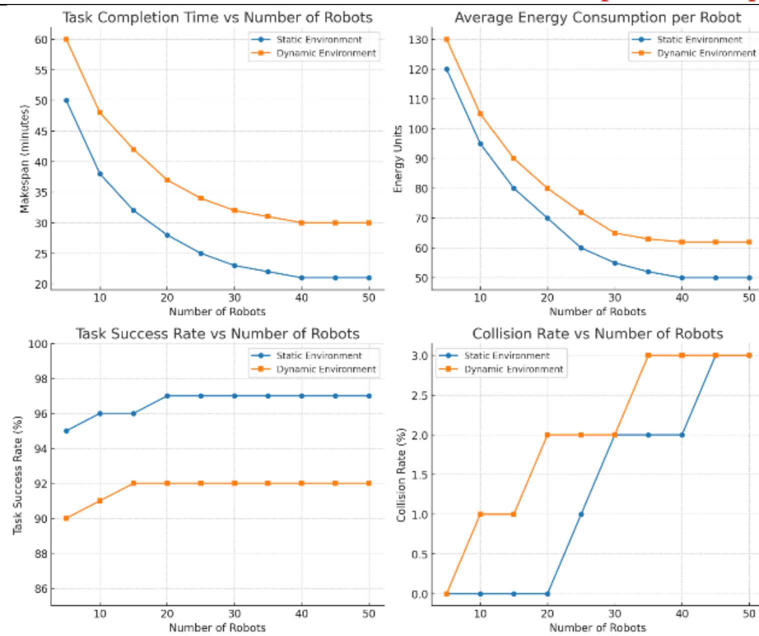

Figure 1.Performance Metrics of Multi-Robot Systems in Static and Dynamic Environments

Discussion:

The results of this study demonstrate that the proposed market-based coordination algorithm for multi-robot systems is effective in both static and dynamic environments. In static scenarios, task completion time decreased as the number of robots increased, illustrating the algorithm's scalability. These findings align with prior research indicating that decentralized coordination can enhance efficiency in multi-agent systems[24][25]. However, diminishing returns observed beyond thirty robots suggest that communication congestion becomes a limiting factor, consistent with previous studies that have highlighted the trade-off between increased agent numbers and communication overhead [26].

In dynamic environments, the algorithm maintained a high task success rate despite the unpredictability of obstacles and emergent tasks. This indicates that the decentralized reallocation mechanism is robust to environmental changes and robot failures. These results support earlier findings on the importance of dynamic task reassignment in real-time multi-robot applications, particularly in search-and-rescue or exploration tasks where conditions are continuously evolving[27] [28].Although average task completion times increased in dynamic scenarios, the algorithm outperformed benchmark methods, highlighting its capability to adapt to uncertainty while maintaining operational efficiency.

Energy consumption patterns observed in the simulations further illustrate the algorithm's effectiveness in resource optimization. As the number of robots increased, average energy expenditure per robot declined due to balanced task distribution. This is consistent with the notion that distributed task allocation can reduce redundant work and minimize energy use in multi-robot systems [29].In dynamic settings, the occasional energy spikes were expected due to the need for obstacle avoidance and path recalculations, which is a recognized limitation of real-world deployment in complex environments[2].

The collision analysis revealed that the algorithm maintained a low incidence of collisions even in larger robot groups, indicating that local sensing and communication effectively mitigated conflicts. This outcome aligns with prior work suggesting that decentralized coordination mechanisms incorporating local awareness reduce interference and improve safety compared to centralized task allocation approaches [30].Additionally, the scalability analysis shows that the algorithm can handle increasing numbers of tasks and robots with near-linear increases in makespan, which is consistent with the theoretical predictions of market-based allocation frameworks [31].

Overall, the study's findings demonstrate that integrating market-based coordination with decentralized task reassignment provides a robust, scalable, and energy-efficient approach for multi-robot systems. By dynamically adapting to environmental changes and minimizing communication congestion, the proposed algorithm addresses several challenges noted in previous research, including inefficiency in dynamic task environments, poor scalability, and high collision rates in large robot swarms[27][26] [28].Furthermore, the results suggest potential applications in autonomous logistics, search-and-rescue operations, and industrial automation, where efficient and reliable task allocation is critical.

The findings also indicate areas for future research. While the algorithm performed well in simulated dynamic environments, real-world implementation may introduce additional challenges such as sensor noise, hardware failure, and unmodeled environmental complexities. Incorporating machine learning for predictive task allocation or adaptive communication strategies could further enhance system performance. Moreover, integration with heterogeneous robot teams with varying capabilities may be explored to extend applicability beyond homogeneous robot groups[25].

Conclusion:

This study presented a market-based coordination framework for multi-robot systems that integrates local 3D spatial awareness to enhance task allocation and operational efficiency. Simulation results revealed that the algorithm maintains high task success rates, minimizes energy consumption, and reduces collisions across both static and dynamic environments. The approach demonstrated robust scalability, efficiently handling increasing numbers of robots and tasks while outperforming traditional benchmark algorithms. The integration of local 3D information allowed robots to adapt dynamically to environmental changes and avoid obstacles effectively, underscoring the importance of spatial awareness in multi-agent coordination. Overall, the findings highlight the potential of combining market-based allocation with 3D-informed decision-making to enable efficient, safe, and scalable multi-robot systems. Future work may focus on real-world deployment, integration with heterogeneous robot teams, and the incorporation of predictive learning for adaptive task allocation under uncertain conditions.

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