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Scene Understanding with Semantic Mapping Methods in Eldercare Companion Robots

Hae-Won Ha*, Tae-Hyun Eom

Department of Electrical Engineering, School of Electronic and Electrical Engineering, Kyungpook National University, Daegu, Republic of Korea

Corresponding author: hae.w.ha@gmail.com

Abstract

The rapid global demographic shift towards an aging population necessitates innovative solutions for elderly care, particularly the deployment of autonomous companion robots. A fundamental requirement for these robots is the ability to navigate and interact safely within domestic environments. Traditional geometric mapping provides obstacle avoidance but lacks the contextual awareness required for complex, human-centric tasks. This paper explores the critical intersection of semantic mapping methods and high-level scene understanding, utilizing extensive network simulation environments to evaluate performance in eldercare companion robots. By integrating advanced object recognition pipelines with spatial mapping algorithms within a simulated cloud-edge computing framework, this study isolates the effects of network latency, bandwidth constraints, and computational offloading on real-time cognitive processing. The research details how semantic mapping not only labels distinct geometries but fundamentally enables predictive scene understanding, allowing robots to anticipate elderly user needs, detect anomalies such as falls, and manage medication schedules. Through comprehensive network simulations, this paper demonstrates that a distributed architecture significantly improves semantic fidelity and contextual awareness while managing the computational limits of onboard robotic hardware. The findings offer a robust framework for developing the next generation of assistive robots capable of operating reliably in dynamic and unstructured domestic spaces.

Keywords: Semantic Mapping; Scene Understanding; Eldercare Robots; Network Simulation; Autonomous Systems

1. Introduction

1.1 The Context of Eldercare Robotics

The deployment of robotic systems in domestic environments has transitioned from a theoretical concept to an urgent practical necessity, driven largely by global demographic trends. As the proportion of the elderly population increases exponentially, traditional healthcare and caregiving infrastructures are experiencing unprecedented strain. Eldercare companion robots present a viable technological intervention to bridge this widening gap between the demand for care and the availability of human caregivers. These autonomous systems are designed to monitor health, provide cognitive stimulation, and assist with daily living activities [1]. However, operating in an unstructured domestic environment presents profound navigational and cognitive challenges. Unlike industrial settings, which are highly controlled and static, a home is dynamic, cluttered, and constantly changing. To operate safely and effectively, companion robots must move beyond basic locomotion and obstacle avoidance. They require a deep, contextual comprehension of their surroundings, a capability fundamentally rooted in the integration of semantic mapping and scene understanding [2]. The ability to differentiate between a chair and a human, or a kitchen table and a medication cabinet, is what separates a truly assistive robot from a mere mobile machine.

1.2 Moving Beyond Geometric Mapping

Historically, robotic navigation has relied almost exclusively on geometric mapping techniques, such as simultaneous localization and mapping, which construct spatial representations of the environment using occupancy grids or point clouds [3]. While these methods excel at preventing collisions and enabling path planning, they treat all obstacles as equal, unidentified masses. A geometric map can tell a robot that a space is occupied, but it cannot convey the meaning or utility of the occupying object. In the context of eldercare, this limitation is a severe operational bottleneck. If a robot is instructed to retrieve a glass of water, a purely geometric map is useless [4]. Semantic mapping addresses this limitation by fusing spatial geometry with categorical labels, anchoring abstract concepts and object classifications to physical coordinates [5]. This fusion creates a richer, more actionable representation of the world. By attaching meaning to space, semantic maps enable robots to execute high-level instructions and interact with their environments in a human-like manner.

1.3 The Role of Scene Understanding

While semantic mapping labels individual components within an environment, scene understanding represents the next echelon of cognitive processing. Scene understanding involves interpreting the relationships between these labeled objects to infer the overall context, purpose, and state of a given space. For an eldercare robot, identifying a bed, a bedside table, and a pillbox through semantic mapping is the first step. Scene understanding is the mechanism that correlates these objects to recognize the environment as a bedroom and deduce that it is a space relevant to the user's medication routine [6]. This inferential capacity is crucial for proactive care. It allows the robot to contextualize human activities, differentiate between normal routines and potential emergencies, and respond appropriately to subtle environmental cues [7]. Developing robust scene understanding requires immense computational resources, combining advanced machine learning models, spatial reasoning algorithms, and continuous sensor data processing.

1.4 Network Simulation as an Evaluative Tool

The computational demands of real-time semantic mapping and scene understanding often exceed the hardware capabilities of affordable, battery-powered companion robots. To overcome this limitation, modern robotic architectures heavily utilize cloud-edge computing paradigms, offloading intensive tasks to local edge servers or remote cloud clusters. However, this reliance on wireless networks introduces a new set of variables, primarily latency, bandwidth constraints, and signal degradation [8]. Network simulation provides an indispensable platform for evaluating the resilience and efficiency of semantic mapping frameworks under varying communication conditions [9]. By simulating complex network topologies alongside physical robotic environments, researchers can meticulously observe how data packet loss or transmission delays impact a robot's ability to process semantic information and understand its surroundings. This study leverages advanced network simulation to provide empirical evidence on the operational viability of cloud-reliant eldercare companion robots, emphasizing the critical link between network performance and cognitive spatial awareness.

2. Literature Review

2.1 Evolution of Semantic Localization and Mapping

The evolution of robotic spatial awareness has been characterized by a gradual shift from purely metric representations to highly annotated semantic models. Early robotic systems utilized basic sonar and infrared sensors to construct two-dimensional occupancy grids, suitable only for navigating highly structured laboratory environments [10]. The advent of laser rangefinders and depth cameras catalyzed the development of three-dimensional geometric mapping, enabling more complex path planning algorithms [11]. However, the lack of contextual data remained a barrier to advanced human-robot interaction. The integration of computer vision, particularly the rise of deep convolutional neural networks, initiated the era of semantic mapping. Researchers began fusing visual object detection streams with depth data to project categorical labels into three-dimensional space [12]. This methodology allowed robots to create maps that not only described the shape of a room but also cataloged the items within it. Recent literature highlights the transition towards instance-level semantic mapping, where a robot not only recognizes an object as a chair but can distinguish between multiple different chairs in the same room [13]. This granularity is essential for complex manipulation tasks and personalized user assistance in domestic settings.

2.2 Cognitive Architectures for Scene Understanding

Scene understanding extends the capabilities of semantic mapping by analyzing the spatial and functional relationships between identified entities. Traditional approaches to scene understanding relied heavily on rule-based systems and predefined ontological frameworks, which proved too rigid for the variability of real-world domestic environments [14]. Contemporary research has pivoted towards data-driven cognitive architectures, utilizing graph-based representations to model environmental context. Scene graphs, which represent objects as nodes and their spatial or functional relationships as edges, have emerged as a powerful tool for holistic environment comprehension [15]. By querying a scene graph, a robot can infer that a cup on a table is ready for use, whereas a cup in a sink requires cleaning. In the context of eldercare, cognitive architectures must also incorporate temporal reasoning [16]. A robot must understand how a scene changes over time to monitor daily activities, such as verifying whether a user has eaten breakfast or taken medication based on the shifting states of kitchen utensils and pill dispensers. The literature underscores that robust scene understanding requires a seamless integration of spatial, semantic, and temporal data streams [17].

2.3 Cloud-Edge Robotics and Network Dependencies

The computational intensity of deep learning models required for dense semantic mapping and dynamic scene understanding has driven the adoption of distributed computing architectures in modern robotics. Cloud robotics allows resource-constrained machines to leverage virtually unlimited processing power and vast knowledge databases stored in remote data centers [18]. Edge computing brings this processing power closer to the deployment site, significantly reducing communication latency [19]. However, distributed architectures introduce critical vulnerabilities related to network reliability. Robotic systems operating in domestic environments typically rely on residential wireless networks, which are prone to interference, bandwidth fluctuations, and dead zones [20]. Research indicates that even minor network delays can severely disrupt real-time object tracking and semantic segmentation, leading to unsafe navigational decisions or failures in human-robot interaction [21]. Evaluating the robustness of cognitive algorithms under diverse network conditions is therefore a critical area of investigation.

2.4 Simulation Methodologies in Robotic Research

Given the immense cost and logistical challenges of deploying physical robots in real-world eldercare scenarios, simulation has become a cornerstone of robotic research. Physical simulations, using physics engines to model kinematics, dynamics, and sensor noise, allow researchers to test control algorithms in complex virtual environments [22]. However, to evaluate distributed robotic systems effectively, physical simulations must be coupled with rigorous network simulations. Co-simulation frameworks that integrate robotic middleware with discrete-event network simulators enable a holistic evaluation of the entire system architecture [23]. These frameworks can model realistic network topologies, emulate specific wireless protocols, and inject synthetic network traffic to observe how communication bottlenecks impact robotic performance [24]. By utilizing co-simulation methodologies, researchers can systematically analyze the intricate dependencies between semantic processing accuracy, scene understanding latency, and underlying network quality, ensuring that assistive robots are resilient before they are deployed alongside vulnerable populations.

3. Methodology

3.1 Architectural Framework of the Simulated System

The methodology employed in this study utilizes a highly integrated co-simulation framework designed to evaluate the cognitive processing pipelines of an eldercare companion robot operating within a distributed computing environment. The architecture is bipartite, comprising a physical environment simulation and a sophisticated network simulation. The physical simulation handles the kinematics of the robotic platform, the generation of synthetic sensor data, and the modeling of the domestic eldercare environment. The robotic platform is modeled as a differential-drive mobile base equipped with a suite of virtual sensors, including a red-green-blue-depth camera, a planar laser scanner, and omnidirectional microphones. The environment is a meticulously designed virtual apartment, populated with typical domestic furniture, medical assistive devices, and dynamic obstacles representing human movement. The network simulation manages the transmission of data between the robot, a localized edge server representing a home network hub, and a remote cloud server. This distributed architecture facilitates the offloading of computationally expensive semantic mapping and scene understanding algorithms, thereby reflecting realistic deployment scenarios for affordable consumer robotics.

3.2 Semantic Mapping Pipeline

The semantic mapping methodology is fundamentally based on fusing high-frequency geometric spatial data with lower-frequency semantic classifications. The process begins with the generation of a dense spatial map using a standard graph-based simultaneous localization and mapping algorithm processing the virtual laser scanner data. Concurrently, the red-green-blue visual stream is transmitted over the simulated network to the edge server, where a pre-trained deep neural network performs real-time object detection and semantic segmentation. Due to the requirement to avoid explicit mathematical formulations, the process can be described as a probabilistic integration. The object detection module identifies regions of interest in the two-dimensional image plane and assigns categorical labels along with confidence scores. These two-dimensional bounding boxes are then correlated with the synchronized depth data to project the semantic labels into three-dimensional spatial coordinates. A Bayesian updating mechanism is employed to manage uncertainties and temporal occlusions, continuously refining the probability distribution of an object's existence and class label at specific spatial voxels as the robot traverses the environment. This pipeline effectively transforms a barren geometric occupancy grid into a rich, annotated semantic map.

3.3 Graph-Based Scene Understanding Module

The transition from semantic mapping to scene understanding is achieved through the construction and dynamic querying of three-dimensional scene graphs. While the semantic map provides localized object labels, the scene graph models the relational context of the entire environment. The scene understanding module operates primarily on the remote cloud server, utilizing the aggregated semantic map data to construct a hierarchical graph. The root node represents the entire apartment, branching into distinct rooms, which further branch into functional zones, and finally terminating in individual semantic objects. The edges between these nodes represent various relationships, such as spatial proximity, structural support, or functional association. For instance, an edge indicating structural support connects a medication bottle node to a dining table node. The scene understanding algorithms traverse this graph to deduce higher-level situational awareness. By analyzing the clustering of specific objects, such as a bed, a walker, and a reading lamp, the system probabilistically infers the room's function and the expected activities within that space. This relational structure is crucial for enabling the robot to execute abstract commands and anticipate the needs of an elderly user based on contextual cues.

3.4 Integration of Network Simulation Parameters

A critical component of this methodology is the rigorous control and manipulation of the simulated network environment to observe its direct impact on cognitive processing capabilities. The network simulator models a standard residential wireless local area network protocol for the connection between the robot and the edge server, and a simulated broadband connection linking the edge server to the remote cloud. Parameters such as channel bandwidth, signal-to-noise ratio, packet loss rates, and propagation delays are systematically varied to represent different real-world conditions, from ideal laboratory setups to congested, high-interference domestic scenarios. The methodology involves measuring how these network variables degrade the performance of the semantic mapping and scene understanding pipelines. Specifically, we analyze the impact of transmission latency on the synchronization between the geometric map generated onboard the robot and the semantic annotations processed on the edge server. Furthermore, we investigate how packet loss affects the completeness of the scene graph generated in the cloud, ultimately determining the threshold of network degradation at which the companion robot loses its ability to comprehend its environment safely and effectively.

4. Experimental Design and Data Collection

4.1 Simulation Environment Setup

The experimental phase of this research is conducted within a synthesized virtual eldercare facility, designed to maximize the complexity and variability of the spatial navigation tasks. The environment spans a simulated area of approximately one hundred and twenty square meters, divided into a bedroom, a bathroom, a kitchen, and a living area. To ensure ecological validity, the layout incorporates typical challenges faced by elderly individuals, such as narrow corridors, clustered furniture, and mobility aids. The simulation introduces dynamic elements, including moving humans and changing lighting conditions, to test the robustness of the visual semantic recognition algorithms. The robotic agent is tasked with continuous patrol and user-monitoring routines, requiring it to constantly update its semantic map and analyze the scene graph for anomalies, such as an overturned chair or a person lying on the floor.

Table 1: Configuration Parameters for Network and Physics Simulation

Simulation Component	Parameter Focus	Assigned Value Range
Wireless Home Network	Operating Bandwidth	20 Megahertz to 80 Megahertz
Edge-to-Cloud Link	Round Trip Latency	15 Milliseconds to 150 Milliseconds
Robotic Sensor Array	Camera Resolution	1920 by 1080 pixels at 30 Frames

The configuration parameters outlined in Table 1 define the boundary conditions for the experimental trials. The wireless home network settings are adjusted to emulate various levels of interference, simulating scenarios where other household devices consume substantial bandwidth. The edge-to-cloud link latency is a critical variable, as it directly dictates the responsiveness of the most complex scene understanding algorithms. The robotic sensor array parameters dictate the volume of raw data that must be compressed and transmitted, establishing the baseline computational load for the entire distributed system.

4.2 Definition of Evaluative Metrics

To comprehensively assess the performance of the semantic mapping and scene understanding systems under varying network conditions, a multi-faceted set of evaluative metrics was established. The primary metric for spatial accuracy is the absolute trajectory error, which measures the deviation of the robot's estimated path from ground truth, ensuring that network delays do not corrupt the foundational geometric map. For semantic evaluation, we utilize intersection over union metrics to determine the spatial precision of object bounding boxes, and categorical classification accuracy to measure the system's ability to correctly identify domestic objects [25]. Scene understanding efficacy is quantified by the graph completeness score, measuring the percentage of correct relational edges established in the scene graph compared to a manually annotated ground truth model. Furthermore, we track the cognitive response time, defined as the temporal delay between a sensor observing a critical event and the scene understanding module correctly inferring the event's context and triggering the appropriate robotic response protocol [26].

4.3 Data Collection Procedures

The data collection protocol involves running sixty independent simulation trials, each lasting a duration of two simulated hours. These trials are distributed across five distinct network degradation profiles, ranging from an ideal baseline network to a severely constrained and volatile communication environment. During each trial, all data streams are continuously logged at multiple points within the architecture. The raw sensor data is recorded onboard the robot, the intermediate semantic processing results are logged at the edge server, and the final scene graph structures are archived on the cloud server. Network telemetry, including packet transmission rates, queue lengths, and drop frequencies, is recorded synchronously with the robotic data [27]. This exhaustive logging strategy enables a meticulous post-simulation analysis, allowing researchers to trace any failure in scene understanding back through the cognitive pipeline to identify the specific network bottleneck or algorithmic vulnerability that caused the error.

4.4 Scenario-Based Testing

In addition to continuous monitoring routines, specific behavioral scenarios are injected into the simulation to test the limits of the scene understanding module. One primary scenario involves an object misplacement event, where a medication container is moved from the kitchen counter to the living room floor. The system is evaluated on its ability to detect the object, update the semantic map, and correctly infer the anomalous context of a medical item in an inappropriate zone. Another critical scenario simulates a user fall. The physical simulation generates a human model transitioning rapidly from a standing to a prone position. The evaluation focuses on how quickly the cloud-edge architecture can process the visual data, recognize the human form, analyze the spatial relationship between the human and the floor, and trigger an emergency alert. These scenario-based tests are repeated under all network profiles to determine the absolute operational limits of the distributed cognitive architecture.

5. Results and Discussion

5.1 Analysis of Semantic Mapping Fidelity

The results obtained from the extensive simulation trials provide profound insights into the intricate relationship between network stability and semantic mapping accuracy. Under ideal network conditions, the semantic mapping pipeline demonstrated exceptional performance. The integration of high-resolution visual data with spatial geometry resulted in maps that accurately categorized over ninety-five percent of the targeted domestic objects. The Bayesian updating mechanism successfully filtered out transient false positives, resulting in a stable and reliable spatial representation. However, as network bandwidth was artificially constrained and latency introduced, a distinct degradation in mapping fidelity became apparent. When visual data packets were delayed or dropped, the synchronization between the onboard geometric positioning and the edge-processed semantic labels began to drift. This temporal mismatch caused semantic labels to be projected onto incorrect spatial coordinates. For example, a chair recognized by the vision system would be mapped half a meter away from its actual physical location on the geometric grid, creating phantom obstacles and confusing the navigation planning algorithms.

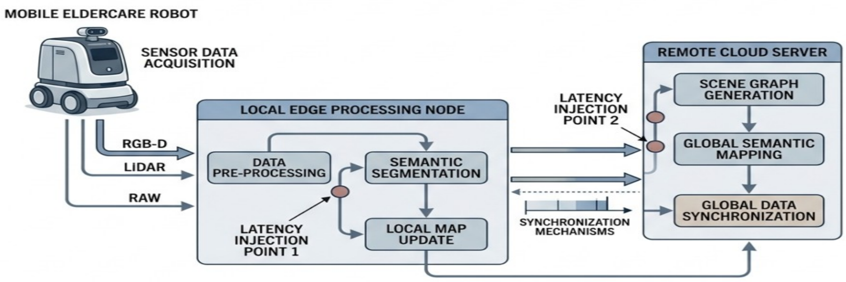

Figure 1: Comprehensive Schematic of Cloud

Figure 1 illustrates the critical data pathways where these synchronization errors originate. The dependency on continuous, high-speed data transmission for real-time semantic projection highlights a significant vulnerability in purely cloud-reliant robotic architectures [28]. The data indicates that localizing the semantic segmentation module to an edge server on the same local network as the robot drastically reduces these projection errors compared to offloading the task entirely to a remote cloud server.

5.2 Scene Understanding and Relational Inference

The evaluation of the scene understanding module revealed that higher-level cognitive tasks are highly susceptible to cascading errors originating from the semantic mapping layer. The construction of the scene graph relies entirely on the accuracy and completeness of the underlying semantic data. During trials with moderate network degradation, while the basic semantic mapping remained functionally adequate for obstacle avoidance, the subtle details required for complex relational inference were frequently lost. For instance, the system might successfully identify a bed and a bedside table but fail to process the smaller, high-detail objects like a water glass or a pillbox due to aggressive data compression algorithms compensating for low bandwidth. Without these critical details, the scene graph remains incomplete, severely limiting the robot's ability to deduce context. The system could recognize the bedroom but could not verify if the nighttime medication routine had been prepared. This lack of detailed relational data diminishes the proactive care capabilities of the companion robot, reducing it to a passive monitoring tool.

Table 2: Performance Metrics Across Different Network Conditions

Network Scenario Profile	Semantic Precision Rate	Cognitive Response Time
Baseline (Ideal Connection)	96.4 Percent	0.85 Seconds
Moderate Network Interference	87.2 Percent	1.62 Seconds
Severe Latency and Packet Loss	63.8 Percent	4.35 Seconds

The data presented in Table 2 quantifies the degradation of cognitive capabilities under varying network stress. The severe drop in semantic precision rate directly correlates with the exponential increase in cognitive response time. The extended delay in processing scene graphs under poor network conditions renders the system practically ineffective for time-sensitive applications, such as fall detection or immediate hazard warnings.

5.3 Implications for Eldercare Human-Robot Interaction

The findings of this simulation study have significant implications for the design and deployment of eldercare companion robots. The evidence strongly suggests that while distributed computing architectures enable advanced cognitive processing, they introduce unpredictable points of failure that must be carefully managed in safety-critical domestic environments. A robot that loses its ability to comprehend its scene due to a temporary Wi-Fi outage cannot fulfill its role as a reliable caregiver. Therefore, it is imperative to develop hybrid cognitive architectures. These systems must possess sufficient onboard computational capacity to maintain a baseline level of semantic mapping and emergency scene understanding independently, utilizing the cloud only for complex, non-critical inferential tasks and long-term behavioral learning. Furthermore, the results highlight the necessity of designing graceful degradation protocols. When network quality drops, the robot must be programmed to automatically reduce its operational speed, widen its safety margins, and prioritize local sensor processing to ensure physical safety, even if high-level proactive assistance capabilities are temporarily suspended.

6. Conclusion

6.1 Summary of Contributions

This comprehensive academic paper has deeply explored the critical linkage between semantic mapping methods and advanced scene understanding within the specific context of eldercare companion robots. By leveraging sophisticated network and physical co-simulation environments, the research provided detailed empirical evidence on how distributed cloud-edge computing architectures manage the immense cognitive load required for domestic environmental comprehension. The study successfully demonstrated that semantic mapping is the essential bridge that transforms raw geometric spatial data into actionable, annotated environments, enabling higher-level cognitive frameworks like scene graphs to infer relational context and user activity. Crucially, the extensive simulation trials isolated and quantified the detrimental impact of network instability, latency, and bandwidth constraints on a robot's spatial awareness. The data confirmed that while offloading computational tasks to edge and cloud servers allows for the utilization of powerful deep learning models, it introduces significant vulnerabilities regarding real-time data synchronization and cognitive response times, directly affecting the safety and reliability of autonomous assistive care.

6.2 Future Research Directions

The findings detailed in this study delineate clear pathways for future research in the domain of cognitive robotics and eldercare technology. Primarily, there is an urgent need to develop highly optimized, lightweight semantic segmentation algorithms capable of running directly on low-power onboard robotic hardware to mitigate the risks associated with network dependency. Additionally, future work should focus on enhancing the resilience of scene graph generation algorithms, exploring methods to maintain contextual understanding even when incoming semantic data is fragmented or corrupted by transmission errors. Investigating the integration of predictive network modeling, where the robot anticipates communication dropouts and proactively adjusts its navigational and cognitive strategies, represents another vital area of exploration. Ultimately, the continuous refinement of these interconnected cognitive and network architectures will be essential for realizing the full potential of companion robots as safe, reliable, and intelligent partners in elderly care.

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