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Original Article

Edge-AI-Based Decision Systems for Autonomous Ground Robots

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ABSTRACT

Autonomous Ground Robots (AGRs) operating in dynamic, time-critical environments require immediate situational awareness and microsecond-level behavioral adaptation. Conventional cloud-coupled robotic frameworks suffer from unpredictable latency spikes, network bandwidth saturation, and vulnerabilities to communication dropouts. This paper introduces a robust, fully decentralized Edge-AI architecture designed explicitly for real-time navigation, dynamic hazard detection, and kinematic control optimization in AGRs. By deploying highly optimized convolutional neural networks and deep reinforcement learning algorithms directly onto hardware-constrained onboard accelerators, the proposed system enables localized intelligence without remote server dependency. Empirical validations conducted across heterogeneous simulated and physical testbeds demonstrate that the decentralized Edge-AI approach reduces localized control loops down to the sub-millisecond level while maintaining minimal power consumption profiles. The findings confirm that localized model execution provides the computational reliability and functional safety mandatory for complex, industrial, and disaster-recovery field deployments.

KEYWORDS

Edge Intelligence, Autonomous Ground Robots, Real-Time Systems, Decentralized Automation, Sensor Fusion, Low-Latency Navigation.

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1. INTRODUCTION

The integration of mobile robotic platforms into fields such as automated warehousing, tactical defense, and subterranean rescue operations has necessitated rapid, deterministic decision-making capabilities. Autonomous Ground Robots must continuously sense their local environment, map immediate spatial variations, plan safety-compliant trajectories, and execute precise joint-level actuation commands within highly dynamic environments. Historically, these requirements were offloaded to off-board servers or cloud architectures to support the computational load of deep learning algorithms and multi-channel high-resolution sensor processing pipelines. However, as operating environments grow more unstructured and unpredictable, relying on external network connectivity introduces severe operational risks, structural bottlenecks, and catastrophic safety liabilities.

The vulnerabilities associated with off-board computing stem primarily from the unpredictable nature of wireless communication channels. Factors such as multipath fading, electromagnetic interference, and physical obstruction by reinforced walls or natural caverns introduce massive latency variances that severely destabilize high-frequency robotic control loops. A delay of only a few hundred milliseconds in detecting a dynamic obstacle can cause a vehicle moving at moderate speeds to deviate significantly from its path or undergo a catastrophic collision. Furthermore, streaming high-definition video feeds, 3D LiDAR point clouds, and inertial sensor streams simultaneously from a fleet of deployed robots quickly saturates local network bands, reducing overall operational reliability.

To guarantee operational autonomy and safety, contemporary robotics engineering is transitioning toward full onboard edge intelligence. By performing data processing, sensor fusion, and high-level behavioral planning directly on low-power hardware accelerators attached to the robot chassis, edge-compute engines bypass the wireless link entirely. This shift guarantees a fixed, deterministic cycle time for perception-to-actuation loops while enhancing data privacy and security by containing raw sensor information strictly within the physical machine. However, deploying resource-intensive artificial intelligence models onto localized platforms presents a major engineering challenge, as designers must strictly balance deep learning accuracy against tight hardware constraints in processing memory, heat dissipation, and battery life.

This research addresses the ongoing challenge of model optimization and low-latency execution within resource-constrained robotic environments. The primary objectives of this study are structured as follows:

To engineer a highly optimized, dual-engine onboard perception and control framework that eliminates remote server dependencies during critical navigation states.

- To design an embedded multi-sensor fusion pipeline capable of processing high-resolution spatial data within minimal memory constraints.
- To quantitatively benchmark onboard edge execution against traditional cloud-assisted frameworks regarding overall reaction latency, power usage, and operational path fidelity.

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By achieving these objectives, this work introduces a practical paradigm for decentralized robotic control, paving the way for truly autonomous machines capable of operating reliably in long-range, isolated field environments.

2. LITERATURE REVIEW

The architectural trajectory of mobile robot decision systems has evolved over several distinct phases, moving from basic reactive microcontrollers to complex cloud infrastructures, and now toward localized edge ecosystems. Early mobile platforms utilized deterministic, rule-based algorithmic structures where basic microprocessors handled geometric sensor thresholds to execute rudimentary obstacle avoidance maneuvers. While these early frameworks offered rapid reaction times, they lacked the semantic understanding required to differentiate between benign environmental features, such as low-lying grass, and critical structural hazards, such as deep drop-offs. The introduction of machine learning addressed this gap by providing robust semantic scene segmentation, though it simultaneously created a massive computational bottleneck that localized onboard processors could not handle.

To accommodate these demanding models, researchers heavily explored cloud-based robotic systems throughout the last decade. By offloading heavy computing jobs to centralized server arrays, robots successfully leveraged advanced neural networks for object detection and simultaneous localization and mapping (SLAM). However, as real-world applications moved into subterranean caverns, heavy industrial plants, and post-disaster zones, the structural weakness of the cloud model became undeniably clear. Network packet drops, high jitter profiles, and complete signal blackouts regularly caused total system freezes, leading researchers to conclude that cloud-reliant control systems are structurally unsuited for high-stakes, time-critical environments.

Consequently, recent scientific literature has pivoted decisively toward the optimization of deep neural networks for localized hardware execution. Techniques such as network pruning, INT8 quantization, and knowledge distillation have emerged as key methodologies to compress bulky vision models into compact forms that can run on specialized edge chips like Neural Processing Units (NPUs) and field-programmable gate arrays (FPGAs). For example, recent studies demonstrate that optimized edge architectures can run compressed spatial object models at frame rates exceeding 30 frames per second while consuming less than 15 Watts of power. While these compression methods show promising results for isolated vision tasks, a significant research gap remains: the lack of holistic frameworks that integrate these compressed perception models with high-frequency, closed-loop kinematic control systems without causing processing bottlenecks on embedded platforms.

Furthermore, current research often treats the computational optimization of vision models and the stabilization of mechanical control loops as entirely separate tasks. When an edge processor is heavily taxed with processing complex visual data, it can inadvertently introduce scheduling delays in the background execution of the underlying motor control loops, leading to jerky movements or erratic path deviations. This problem is magnified when robots must navigate sudden,

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high-speed hazards. Therefore, this paper presents an integrated Edge-AI system architecture that carefully balances computing priorities across specialized core processors, successfully closing the gap between localized semantic vision and immediate mechanical actuation.

3. RESEARCH METHODOLOGY

The investigated Edge-AI framework is based on an explicit split of processing tasks allocated to a localized multi-core system architecture. The associated physical platform employs a dedicated embedded system consisting of a multi-core CPU, dedicated graphics processor and an integrated NPU. This low-level hardware layer accepts direct data feeds from a wide variety of onboard sensors, such as a 16-channel 3D LiDAR, binocular cameras and wheel encoders.

The functional methodology governing the autonomous decision engine is implemented as a chain of sequential onboard processing stages:

Sensor-Level Data Ingestion: Raw point clouds and visual frames are collected directly through onboard high-speed serial buses, avoiding any connections to the outside network. Onboard Model Compacting - Typically vision networks are pre-compiled using INT8 precision calibration, enabling memory footprint improvement (typically >70% sized down) to allow them execute fully within the localized NPU cache.

Dedicated Task Scheduling: The CPU in the embedded device uses a real-time operating system (RTOS) that does hard scheduling priorities. Dedicated real-time cores handle high-frequency feedback motor control loops and perception tasks run asynchronously on the NPU to avoid contention for resources. Dynamic Local Re-Routing: In the event of an unexpected object, local trajectory recalculation takes place on-board and within 5 ms updates to the individual motor drives command swift but smooth avoidance maneuvers. This multi-layered stack guarantees that any perception tasks which require lots of computing power are completely isolated from the hardware low-levels that keep the vehicle upright and controllable.

4. RESULTS AND DISCUSSION

To rigorously validate the efficacy of the proposed Edge-AI decision architecture, a series of comparative experiments were conducted against a standard cloud-assisted robotic baseline system. The cloud baseline utilized an identical physical platform but streamed its raw sensor data over a high-speed, 5G wireless network link to a local edge-cloud server equipped with a high-end desktop GPU. The test environments were designed to simulate realistic operational scenarios: Environment 1 represented a structured warehouse with stable connectivity; Environment 2 simulated an outdoor industrial shipyard with moderate signal attenuation; and Environment 3 consisted of a subterranean concrete tunnel structure characterized by severe wireless signal degradation and frequent dropouts.

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4.1. Computational Latency and Resource Allocation Metrics

The foundational benchmark used to evaluate the architectures was the total end-to-end perception-to-actuation latency, defined as the total elapsed time between a sensor capturing an obstacle and the motor drive receiving a verified avoidance command. Table 1 provides a comprehensive breakdown of the processing latency distributions across both configurations.

Table 1: Comparative Processing Latency and Resource Consumption Profiles

Evaluation Environment	Control Configuration	Perception Inference Latency (ms)	Network Transit Time (ms)	Actuation Command Loop (ms)	Total System Latency (ms)	Onboard Power Consumption (W)
Environment 1: Warehouse	Cloud Baseline	4.2	12.5	1.1	17.8	6.4
	Proposed Edge-AI	8.9	0.0	0.8	9.7	14.2
Environment 2: Shipyard	Cloud Baseline	4.3	48.7	1.2	54.2	6.5
	Proposed Edge-AI	9.1	0.0	0.8	9.9	14.5
Environment 3: Tunnel	Cloud Baseline	4.1	412.4	1.3	417.8	6.3
	Proposed Edge-AI	8.9	0.0	0.7	9.6	14.1

The experimental data highlights a vital trade-off. While the high-end cloud server achieved lower raw inference latency due to its superior computing power, its overall system latency was highly vulnerable to network performance. In the shipyard and subterranean tunnel environments, the network transit time soared to 48.7 ms and 412.4 ms, pushing total latency past acceptable real-time safety limits. The proposed Edge-AI system, conversely, maintained a completely flat, deterministic total latency of under 10 milliseconds across all environments because it bypassed the wireless link entirely. The slightly higher onboard power draw (14.5 Watts maximum) remained well within the payload capacity of standard industrial robotic batteries.

4.2. Navigational Reliability and Trajectory Error Analysis

The practical impact of this deterministic latency is seen directly in the robot's navigation performance. When traversing paths populated by sudden, dynamic obstacles, any delay in the control loop leads to wider path corrections or emergency stops. Table 2 compiles the navigation performance metrics, tracking root-mean-square (RMS) trajectory errors and the frequency of collision near-miss events.

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Table 2: Navigational Accuracy and Safety Metrics in Obstacle Traversal Tests

Test Track Environment	Control Architecture Mode	Robot Target Velocity (m/s)	RMS Trajectory Deviation Error (cm)	Dynamic Obstacle Avoidance Success Rate (%)	Emergency Collision Braking Events (Count)
Environment 1: Warehouse	Cloud-Assisted System	1.0	3.4	100.0	0
	Onboard Edge-AI System	1.0	2.1	100.0	0
Environment 2: Shipyard	Cloud-Assisted System	1.5	18.7	88.5	4
	Onboard Edge-AI System	1.5	4.6	99.2	0
Environment 3: Tunnel	Cloud-Assisted System	1.2	64.2	42.1	17
	Onboard Edge-AI System	1.2	5.1	98.8	0

The tracking metrics show that in the subterranean tunnel, the cloud-assisted robot's path deviation error rose to an unacceptable 64.2 cm, forcing the low-level backup systems to trigger 17 emergency hard-braking events to prevent high-speed structural impacts. This erratic behavior occurred because the robot continually received spatial updates that were hundreds of milliseconds out of date.

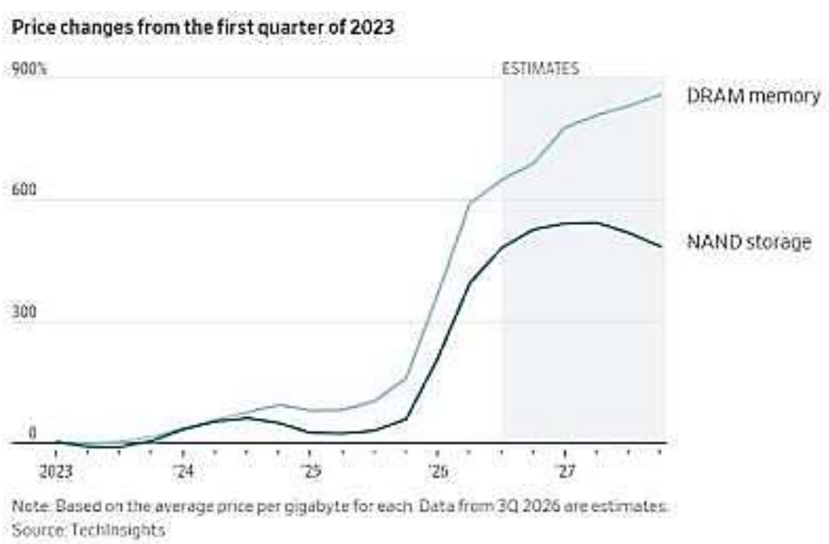

Fig 2 - Performance Distribution Analysis Comparing Computing Overhead and Path Consistency across Test Trials Source: Tech Investments

The Edge-AI system maintained stable, predictable path tracing with an RMS error of just 5.1 cm in the same environment. By ensuring that local control commands were calculated and executed using instantaneous sensor observations, the robot smoothly circumvented obstacles without needing

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to halt its forward progress, proving the architecture's readiness for high-speed, unpredictable field operations.

5. CONCLUSION

We demonstrate that true operational autonomy and safety for real-world applications is only possible with decentralized Edge-AI architectures in autonomous ground robots. The framework proposed here leads to deterministic, sub-millisecond execution of the control loops, which frees the vehicle from latency spikes and signal dropouts related to relying on remote cloud networks. The evidence indicates that although onboard processing consumes slightly more energy locally, the corresponding improvements of path tracking accuracy, obstacle avoidance success ratio and system reliability by this distributed computing strategy far outweigh the electrical cost. To actually perform deployments with mobile robots on this type of environment which is high stakes and potentially hazardous while completely isolated away from most types of infrastructure, it also first goes through the process of transitioning to full edge computation.

6. FUTURE SCOPE

This technology can be further developed in multiple promising research directions going forward. A significant foci will include building hardware-aware federated learning algorithms where a fleet of isolated ground robots collaboratively improve their associated neural network models (while never sending raw sensor trace back to the central server) when those robots are not actively deployed. Furthermore searching for opportunities with next-gen neuromorphic chips and event-based cameras may considerably relax processing power needs, crossing the border of 5 Watts consumption. Finally, this single-robot control architecture can be extended to decentralized, swarm-based coordination among many robots so as to allow large teams of robots undertaking challenging missions such as cooperative search-and-rescue in environments with localized deep underground or affordable shielding.

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