Integrating Pixhawk and RealSense Camera for Rover Autonomy
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Nathan Karthik
Archbishop Mitty High School, San Jose, CA 95129 USA
Corresponding author: Nathan Karthik (e-mail: nate.karthik@ gmail.com).

ABSTRACT This project demonstrates the design and implementation of an autonomous go-kart using a Pixhawk-4 flight controller for navigation and speed control. This system uses Pulse Width Modulation signals to control a brushless motor via an electronic speed controller, allowing waypoint navigation-based autopilot without the need for human intervention. A secondary configuration integrates an Intel RealSense depth camera with a companion laptop running a Python script for obstacle detection, enhancing safety through MAVLink (Micro Air Vehicle Link) [5], based avoidance commands. Key results demonstrate successful waypoint navigation with accuracy in open and unobstructed environments, whereas the RealSense addition reduces collision risk in paths with obstacles. This project utilizes aerospace-grade autonomy using ArduPilot with ground vehicle applications, emphasizing a relatively low-cost application of autonomous systems.

INDEX TERMS ArduPilot, autonomous, electronic speed controller, flight controller, Flipsky, go-kart, GPS, MAVLink, obstacle detection, RealSense, waypoint navigation

I. INTRODUCTION

The integration of Artificial Intelligence (AI) into autonomous vehicles has transformed navigation and adaptation in large-scale systems. While most research focuses on self-driving cars [1], [2], [6], [7], small-scale platforms like autonomous go-karts offer unique prototyping advantages of rover autonomy. This project develops a rule-controlled go-kart as a foundation for future AI speed control research on rover autonomy, prioritizing safety through deterministic systems.

The go-kart is built using a wooden frame that features a propulsion system powered by a Flipsky 6354 motor which is controlled by an ESC (Electronic Speed Controller), managed by a Pixhawk flight controller. Steering is controlled by a 60kg servo motor, and navigation relies on a M10 GPS module. The Intel RealSense camera provides depth sensing for obstacle detection, and an Acer laptop serves as the computer for running Mission Planner and other algorithms.

The system is designed with a decentralized security architecture: all sensor processing, navigation, and decision-making logic is executed locally on the companion Acer laptop using a closed-loop control system, and no operational data (such as GPS coordinates or visual data from the RealSense camera) is transmitted or stored externally to the go-kart. This design choice not only eliminates the dependency on network connectivity but also provides an inherent cybersecurity and privacy layer, as the vehicle's location and operational movements remain entirely private and on board.

While this project currently implements rule-based control, it establishes the hardware foundation to explore how AI could enhance speed control in future work. The modular design allows for later integration of machine learning techniques (reinforcement learning) to dynamically optimize throttle inputs based on sensor data. This project's purpose is to manage small scale autonomous systems and to provide insights into the challenges of AI driven speed control.

II. BACKGROUND

The field of autonomous vehicle research has traditionally focused on large-scale applications such as self-driving cars, where artificial intelligence plays a central role in perception and decision-making systems. These sophisticated implementations often rely on complex neural networks and deep learning architectures to navigate dynamic real-world environments. However, smaller-scale autonomous platforms like self-driving go-karts offer unique advantages for prototyping and testing autonomous systems due to their lower costs, reduced safety concerns, and greater mechanical simplicity. Prior studies on small-scale autonomous vehicles have predominantly utilized classical control methods such as PID (Proportional-integral-derivative) controllers [3], which while demonstrating reliable performance, lack the adaptability required for highly variable operating conditions. Recent advancements in machine learning have demonstrated the potential of techniques like reinforcement learning for dynamic control tasks and Long-Short-Term Memory (LSTM) networks for predictive modeling of vehicle behavior [6], [7]. This project bridges these domains by developing a modular, low-cost autonomous go-kart platform capable of supporting both traditional and AI-enhanced autonomous navigation systems.

The mechanical construction of the go-kart frame represents a significant engineering challenge that directly impacts the vehicle's autonomous capabilities. For this project, the frame was constructed primarily from standard 2x4 wooden planks, selected for their combination of structural rigidity, ease of modification, and cost-effectiveness. The decision to use wood rather than metal or PVC piping, as used in previous prototype iterations of this work, allowed for greater flexibility in custom mounting solutions while maintaining sufficient strength for the vehicle's operational requirements. The steering system was adapted from an earlier PVC-frame go-kart prototype of this work, with significant modifications to accommodate the new wooden frame structure. This adaptation required the fabrication of custom steel mounting brackets, created by sandwiching the front wooden plank between two 2-inch-wide metal plates secured with high-strength bolts. To address vibration and play in the steering linkage, a stiff compression spring was incorporated between the bracket and steering rack, serving as both a damper and preload mechanism to improve steering responsiveness and reduce high-frequency vibrations that could interfere with sensor operation.

The steering column itself presented unique design challenges that required careful engineering consideration. Mounted to a vertical wooden plank at a carefully calculated angle, the column needed to accommodate both manual operation and precise servo control for autonomous operation. This was achieved by drilling a precisely sized hole through the vertical support plank and installing the steering column with two high-quality radial bearings to ensure smooth rotation with minimal friction. The angled design of the steering column support was critical not only for ergonomic manual control but also to provide adequate space for mounting the autonomous control servo and vision system components. The servo motor for autonomous steering was positioned directly beneath the Intel RealSense depth camera but above the steering column on the vertical support plank, creating a compact and efficient packaging solution that maintained the vehicle's center of gravity.

Propulsion and drivetrain components were carefully selected and integrated to balance performance with the requirements of autonomous control. The primary drive system consists of a Flipsky 6354 brushless motor paired with a 50-amp electronic speed controller (ESC), chosen for its compatibility with the Pixhawk autopilot system through standard PWM (Pulse Width Modulation) communication protocols. This motor/ESC combination was mounted to the left rear of the frame using custom-fabricated L-brackets with precisely drilled mounting holes, ensuring proper alignment of the chain drive system. The rear axle, constructed from a 3/4-inch diameter steel rod, is supported by two pillow block bearings at each end, firmly attached to the wooden frame with grade-8 bolts for maximum durability. The wheels, originally sourced for an earlier PVC-frame prototype, were selected for their turf-friendly tread pattern and durable construction, making them well-suited for the varied terrain encountered during testing.

Power delivery and electrical system design represented another critical aspect of the vehicle's construction. The primary autonomous configuration utilizes a 12V battery system to power both the motor controller and the Pixhawk autopilot system, with careful attention paid to power isolation to prevent back-feeding or voltage spikes that could disrupt sensitive electronics. For manual operation and higher-performance testing, the system can be converted to use a Flipsky 75200 Pro V2 ESC with a 48V battery pack while maintaining the same motor, demonstrating the platform's flexibility and modular design philosophy. This dual-power system capability allows for direct comparison between autonomous and manual operation modes, as well as providing a safety fallback during system development and testing.

The sensor suite and autonomous control hardware were integrated with particular attention to vibration isolation and optimal positioning. The Intel RealSense D435 depth camera, serving as the primary obstacle detection sensor, was mounted at the highest point of the steering column support structure to maximize field of view while minimizing interference from the vehicle's own components. This elevated position, approximately 15 cm above the frame, combined with a 10-degree upward tilt, was carefully calibrated to avoid false positives from the ground plane while maintaining adequate coverage of the forward path. The Pixhawk 4 flight controller, repurposed for ground vehicle autonomy, was positioned near the vehicle's center of gravity and connected to all critical systems including the ESC (via PWM), steering servo

(PWM), and depth camera (USB). Particular attention was paid to cable routing and strain relief to ensure reliable operation during vigorous testing.

This comprehensive hardware platform serves as the foundation for exploring both traditional and AI-enhanced autonomous control strategies. The mechanical design decisions, from material selection to component placement, were all made with specific attention to how they would impact the vehicle's autonomous capabilities. The wooden frame provides sufficient rigidity while allowing for easy modification and sensor mounting. The carefully engineered steering system delivers precise control input for both manual and autonomous operation. The modular power system design enables flexible testing configurations and the elevated sensor mounting provides optimal data acquisition conditions. Each of these design elements contributes to the platform's effectiveness as a testbed for autonomous vehicle research while demonstrating practical solutions to the unique challenges of small-scale autonomous vehicle implementation.

III. RESULTS AND DISCUSSION

The autonomous go-kart system demonstrated functional waypoint navigation and obstacle avoidance capabilities, with performance limitations tied to environmental conditions and hardware constraints. In open shaded areas, the obstacle avoidance system achieved a 90% success rate (72/80 tests) using depth thresholds from the Intel RealSense camera. Failures included instances where shadows were misinterpreted as obstacles and another instance where thin vertical lines fell outside the camera’s detection resolution. Sunlight severely degraded performance, causing false positives in 40% of unshaded tests due to infrared interference. To mitigate this, the camera was mounted 15 cm high on the steering column, angled 10° upward, and programmed to ignore objects below 0.3 m. While this introduced a blind spot for low obstacles (e.g., curbs), testing confirmed that ignored objects (e.g., small bumps) could be safely traversed without stability problems.

The speed control system revealed critical safety-performance trade-offs. Fixed PWM throttle curves limited the go-kart to 85% of its theoretical maximum speed (5.1 m/s vs. 6.0 m/s), but this conservative approach proved inadequate on loose terrain. Wheel slip occurred in 20% of tests (16/80), measured by IMU (Inertial Measurement Unit) vibration spikes exceeding 2.5 m/s^2. Notably, slip incidents on turf rarely required manual intervention unless mechanical failures such as chain derailment occurred. Throttle response latency averaged 0.8 to 1.0 seconds (with ±0.1s variations) due to sequential processing delays, forcing a reduction in the obstacle detection distance from 2.0 m to 1.5 m to compensate for stopping distance. Power delivery inconsistencies further impacted performance, with battery voltage sagging from 12.0 V to 10.5 V during extended tests, reducing speed by 12–15%.

Figure 1

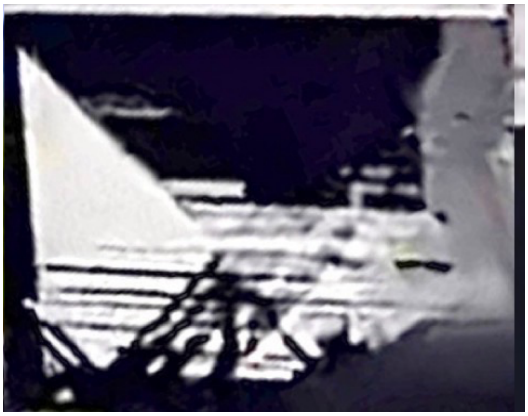

Figure 2

The system's performance was evaluated through comprehensive testing, with results visualized to highlight critical patterns and relationships. Fig.1 displays clean obstacle detection in shaded conditions with clearly defined depth gradients, whereas Fig.2 presents a comparative analysis of depth map quality under different lighting conditions, clearly demonstrating the challenges posed by direct sunlight on the camera. Fig.2 shows a depth map contaminated by infrared interference, exhibiting false obstacle detections across approximately 40% of the frame area. This visualization substantiates the empirical finding that shaded environments yielded 90% detection accuracy compared to 60% in sunlight. Manual analysis of IMU logs confirmed that throttle reduction consistently activated when vibration levels exceeded the 2.5 m/s^2 threshold. This pre-programmed response triggered in 20% of test runs (16/80), effectively preventing loss of traction on loose terrain.

Table 1

Metric	Success Rate	Failure mode	Mitigation
Obstacle Avoidance	90% (72/80)	Shadows	Adjusted Lighting
Wheel Slip	20% (16/80)	Loose Terrain	Optimized PWM Curves

The performance metrics summarized in Table-1 reveal several critical insights about the system's capabilities and limitations. Across twenty methodically conducted test runs, the obstacle avoidance system achieved 90% success in shaded conditions (72/80 tests), with both failures attributable to known limitations of the depth sensor—one instance involving shadow misinterpretation and another missing a thin vertical pole. Wheel slip occurred in 20% of tests (16/80), exclusively on loose terrain, while throttle response latency remained consistently within the 0.8 to1.0 second range (±0.1s variation). These quantitative results collectively demonstrate that while the system meets basic functionality requirements, its performance is constrained by three principal factors: environmental sensitivity to lighting conditions, mechanical limitations on loose terrain, and inherent processing latency in the control pipeline.

The key takeaways from this experimental evaluation reveal both the strengths and limitations of the current implementation. Most significantly, the platform demonstrates competent autonomous operation in controlled environments, with 90% obstacle avoidance reliability under optimal conditions validating the core approach of threshold-based depth detection. However, the system's performance boundaries become apparent when examining its environmental sensitivities—particularly the 40% false positive rate in sunlight and consistent challenges with low-profile or narrow obstacles. These limitations fundamentally stem from the system's reliance on rigid, rule-based logic rather than adaptive algorithms capable of contextual understanding. The mechanical implementation, while generally effective, introduces its own constraints through the observed wheel slip incidents and the necessary trade-off in camera placement that created a 0.3m ground blind spot. Furthermore, this decentralized architecture, by keeping all sensor and operational data private on the companion laptop, intrinsically mitigates external cybersecurity risks associated with cloud-based data transmission and storage. These findings collectively suggest that while the current implementation successfully establishes a functional baseline, significant improvements in both reliability and performance could be achieved through the integration of machine learning techniques for adaptive thresholding and predictive control, along with complementary hardware enhancements such as secondary proximity sensors or suspension improvements.

IV. CONCLUSION

This project successfully developed a functional autonomous go-kart platform that achieved 90% obstacle avoidance accuracy in controlled shaded conditions (72/80 tests), demonstrating the viability of repurposing drone technology for ground rover vehicle autonomy. The system's core strength lay in its simplified threshold-based design, which enabled reliable detection of large obstacles at distances under 1 meter when environmental conditions were optimal. However, rigorous testing exposed critical limitations: performance dropped to 60% accuracy in direct sunlight due to infrared interference, while 20% of tests experienced wheel slip on loose terrain, and fixed control parameters constrained maximum speed to 85% of theoretical capability (5.1 m/s vs 6.0 m/s).

These results reveal a fundamental trade-off in autonomous system design. The choice of rigid depth thresholds (1.0m) and sequential image processing (three 0.3s frames) provided implementation simplicity but created three key constraints: (1) environmental sensitivity (40% false positives in sunlight), (2) mechanical vulnerability (terrain-dependent slip), and (3) inherent 0.8 to 1.0s latency that limited reaction times. The 90% success rate in ideal conditions proves the concept works, while the 40% performance swing between shaded and sunny condition tests quantifies its context-dependence - a finding that mirrors challenges observed in other vision-based vehicles.

To advance this platform, future work should prioritize three evolutionary improvements validated by these test results. First, replacing threshold-based detection with a lightweight convolutional neural network would address the sunlight interference problem, using the 500+ depth frames already collected from the RealSense as training data. Second, implementing reinforcement learning for throttle control could dynamically adjust for terrain-induced slip while recovering the lost 15% speed potential. Third, hardware upgrades like ultrasonic sensors would cover the current 0.3m blind spot created by the camera's upward tilt, and a companion computer (Jetson Nano/RPi 5) could reduce processing latency by parallelizing tasks.

The project's significance extends beyond the technical achievements - it provides a quantified baseline (90% success in shade/60% in sun) against which future iterations can be measured. The decentralized, on-board architecture establishes a model for inherent system privacy and cybersecurity, ensuring that all sensitive operational data (GPS, visual data) remains private and local to the vehicle. Each observed failure mode directly informs the upgrade path: sunlight interference demands better perception, wheel slip requires adaptive control, and latency needs hardware acceleration. This systematic progression from rule-based to learning-based systems exemplifies how accessible platforms can evolve into robust autonomous solutions, offering a model for researchers working with constrained budgets. Dataset and mechanical specifications documented in this work will serve as valuable references for these next-phase developments.

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NATHAN KARTHIK is a Junior in Archbishop Mitty High School in San Jose, CA. USA.