JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)

Volume 3, Issue 1, 2025
https://jecir.com/

DESIGN AND CONTROL OF AN AUTONOMOUS DRONE NAVIGATION SYSTEM USING EMBEDDED AI

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ABSTRACT

This research study the design and the development of an autonomous drone navigation system utilizing embedded artificial intelligence (AI) capable of real-time decision making, obstacle avoidance, and path planning. The focus of this research is the application of neural networks and reinforcement learning techniques integrated with the drone's onboard computer and the fully autonomous navigation of the drone in sophisticated and rapidly changing environments. The stability, precision, and flexible response of the drone's navigation system within the complex environmental frameworks is attained by the combination of classical control methods (PID, LQR) and the control frameworks provided by artificial intelligence. Other than the developments in the optimization of path planning algorithms (A*, RRT) the paper discusses the incorporation of AI for dynamic obstacle avoidance which enables real-time handling of rapid environmental changes. A balanced coverage of sensor fusion methods (EKF, SLAM) which provides accurate localization in environments where GPS is not available outlines the importance of localization in autonomous drones. The research is developed and demonstrated in multiple environments, and the system's performance is evaluated based on speed, accuracy, and reliability in comparison with classical systems. This research has significance in demonstrating the operationalization of embedded AI with real-time decision making in improving drone autonomy for applications in delivery, surveillance and, search-and-rescue missions.

Keywords: Autonomous Drones, Embedded AI, Navigation Systems, Reinforcement Learning, Path Planning, Obstacle Avoidance, Sensor Fusion, Real-Time Decision Making

INTRODUCTION

A. Background

In recent years, drone technology has rapidly evolved and been integrated into various industries such as mapping, agriculture, surveillance, and even delivery. Drones, or unmanned aerial vehicles (UAVs), are equipped with different sensors, cameras, and other devices, enabling them to accomplish tasks that were difficult or nearly impossible for crewed vehicles to achieve [1]. Drones are able to capture real-time video and images over vast areas and are invaluable to security personnel and law enforcement surveillance operations. Drones are able to deliver packages to customers, fundamentally, transforming delivery services as companies like Amazon rapidly develop packages for autonomous drones [2]. For the agriculture sector, their main use is to assist in the evaluation of crops to develop and manage irrigation systems, and accurately assess the use of fertilizers, thereby reducing costs and improving efficiency [3]. Drones have also transformed mapping and surveying as they are able to develop precise and current geographical data in remote or perilous areas [4].

The ability of drones to perform various tasks without human control significantly improves their efficacy. Sensor suites, control algorithms, and decision-making systems facilitate the highly automated navigation of drones, thereby leading to complete autonomy [5]. Situations where it would be dangerous for people to oversee the drone directly, like during search-and-rescue operations, infrastructure inspections, or agricultural field surveys are of primary such automated functions [6]. Nonetheless, the quest for reliable navigation autonomy is far from solved, as it needs systems to sort and analyze various data sets from disparate sensors in real-time.

The addition of embedded AI technology is essential for enhancing the autonomy of drones. Embedded AI is the machine learning frameworks implemented on the drone. This technology enables the drone to make real-time autonomous decisions by analyzing sensor information without communicating with distant servers [7]. Such technology serves the drone autonomy in real-time applications to function without communicating with bordering systems for constant transmission which is crucial for self-governed deliveries, and self-directed explorations in areas where GPS is not available [8]. Embedded AI allows drones to preform real-time decision-making, path-planning, object detection, collision avoidance and considering all parameters in real-time to conserve power [9]. Developments in AI technology and hardware facilitate the use of sophisticated embedded AI models on small, low power consuming processors, making AI drones widely applicable in numerous scenarios [10].

B. *Problem Statement*

Even with advancements in drone technology, autonomous navigation systems are still confronted with difficulties, particularly in real time processing, avoidance of obstacles, and environmental factors. The challenges posed by the complexity of real-time data cursorily arise from the need for drones to synthesize data gleaned from various sources including cameras, LiDAR, and IMUs. Efficient, powerful and real-time systems must be onboard, yet the AI algorithms remain rudimentary to the systems due to overwhelming resource requirements posed by weight, size and power constraints. Moreover, the limitations in the computing power required for high stake tasks such as path determination and decision making as well as object avoidance have to be streamlined to ensure there is little to no lag, particularly during high-speed maneuvers. Environmental factors also constitute a major problem to the performance of the drones. Take for example, the navigation challenges posed by GPS denied environments such as enclosed spaces, urban canyons, and areas with signal interference, making it difficult for drones to utilize the traditional GPS systems. Here, drones must rely on vision-based navigation systems, which are more prone to challenges such as poor illumination and motion blur, leading to greatly increased computational costs, and increased likelihood of errors arising from poor sensor calibration and fusion.

C. *Objective*

This research aims to devise a drone navigation system capable of autonomous function in intricate settings, employing embedded AI. The system must be capable of autonomous navigation, using real-time sensor information, and AI-powered algorithms to make real-time decisions. The research will prioritize the development of effective control algorithms and the incorporation of AI models for obstacle avoidance, route navigation, and real-time decision-making. Furthermore, the research will seek ways to embed AI within a drone's onboard system to diminish dependence on external computing, thereby enhancing autonomy. This research aims to advance more dependable and effective autonomous drone systems by addressing the previously described challenges particularly those involving real-time data processing, the surrounding environment, and obstacle avoidance. Potential applications of these systems include autonomous delivery, surveillance, agriculture, and search-and-rescue operations.

D. *Scope of the Study*

This study aims to create a drone navigation system which incorporates embedded AI, whereby the drone can operate autonomously in complex environments. The system must operate without human interference by utilizing AI algorithms and sensor data analysis to make real-time decisions. The primary goal will be the development of control algorithms and the integration of AI models which will perform obstacle detection, route planning, and real-time decision-making. Further, the research will attempt to investigate the integration of AI within the drone computing to limit dependence on external processors to enhance operational autonomy. The work contributes to building reliable and efficient autonomous drones for complex real-time operational environments by overcoming the identified challenges in real-time data processing, environmental conditions, and obstacle avoidance. Target sectors for autonomous drones include delivery, surveillance, agriculture and search and rescue missions.

E. *Research Questions*

RQ1: How can AI be effectively embedded into drones for real-time autonomous navigation?
RQ2: What are the key design challenges in embedded AI for drone navigation?
RQ3: How can embedded AI improve the autonomy and performance of drones in dynamic environments?

F. *Significance of the Study*

This research underlines the growing importance of autonomous drone technologies, specifically drones that use artificial intelligence and embedded system technologies. With the development of a self-contained, embedded AI powered, real time autonomous navigation system, this research will allow drones to perform fully autonomous real time tasks without external computational delinking for the first time. This breakthrough will be invaluable in the delivery, surveillance, agriculture, and search and rescue sectors, where drones are employed for rapidly changing and complicated workflows. This research will be instrumental in demonstrating the efficiency, reliability, and versatility of embedded AI in dynamic drone applications to improve drone adaptability across various workflows.

LITERATURE REVIEW

A. *Autonomous Drone Navigation*

Here, decision-making, activity execution, and data assessment real-time tasks performed by onboard sensors are created to define autonomous drone performing navigation. For autonomous navigation, there exist an array of technologies, each presenting a specific set of benefits and drawbacks [11]. Among the most prevalent is GPS-based navigation, which cloud users GPS's satellite signals to determine the drone's location [12]. While GPS navigation delivery near real-time precision outdoors, it has challenges indoors and in GPS-denied surroundings such as urban forests, canyons, and dense suburbs. The situation opens new opportunities for vision-based navigation technologies where drones empowered by cameras and computer vision algorithms identify and avoid obstacles [13]. Through machine vision and advanced image processing algorithms, drones generate real-time contour maps of their environment, a necessity for them to detect obstacles of navigation and track moving targets.

In autonomous drone navigation, sensor fusion also plays a significant role. This technique involves the integration of multiple sensors, including LiDAR, IMUs, cameras, and ultrasonic sensors, to improve the drone's environmental perception. Sensor integration helps the system compensate for the individual weaknesses of the sensors; for example, the range limitation of ultrasonic sensors and the cameras' performance in poor lighting [14]. Another technique, which has gained prevalence particularly in drone navigation for environments lacking GPS, is simultaneous localization and mapping or SLAM. The SLAM algorithm allows the drone to both map an unknown environment and track its position in real-time. While implementing SLAM is beneficial in many situations, the heavy computational requirements pose a problem for real-time usage. The challenges posed by SLAM don't mean that navigation systems offer no challenges. Problems occur with GPS-based navigation in cities, as the signal becomes weak or blocked [15]. Vision-based systems also have challenges and can be negatively impacted by low light or fog. Sensor fusion and SLAM improve navigation systems; however, their lack of computational capacity can prevent the system from functioning in real-time [16].

The challenges described above highlight the necessity of further advancements in algorithms, sensors and the computational architectures that provide the basis for dependable and effective autonomous navigation for drones.

B. Embedded AI in Robotics

Embedded AI refers to the installation of artificial intelligence in hardware units to perform intelligent tasks locally without the use of cloud computing or remote servers. An example of the use of Embedded AI in autonomous systems is deployed drones where real time and low latency decision making is system critical [17]. The use of embedded AI in robotics particularly drones allows them to perform tasks in changing environments autonomously. They can respond to real time modifications and execute tasks without waiting for commands from the external control systems. Embedded AI-equipped systems perceive sensed information and analyze it in real time without the need of external communicative systems. This leads to reduced delays and higher system general performance [18]. The principal AI driven technologies used in embedded systems are neural networks, reinforcement learning and support vector machines. Neural networks, and particularly the deep learning models, are instrumental for drones as they need to recognize various objects, detect obstacles, and analyze numerous streams of visual data coming from cameras and sensors. Image classification and object detection tasks are primarily carried out by deep convolutional neural networks [19]. These networks assist drones in making environment understanding and decision making tasks. In reinforcement learning, the machine learning system advances by interacting within its environment.

Autonomy of drone systems has been increasingly facilitated through embedded AI technologies. However, there are issues that AI embedded technologies face. One of the most important issues is the balancing act between the drone systems' size, weight, and power constraints and the AI algorithms' computational requirements [20, 34]. Embedded systems are inherently resource constrained. Therefore, employing AI on embedded systems requires the embedded systems optimization and the possible inclusion of advanced and dedicated systems such as FPGAs and NVIDIA Jetson SoCs. Such systems provide real-time and embedded decision-making capabilities, yet the quest for advanced power and resource balance continues in robotics AI systems.

C. Navigation and Control Algorithms

Autonomous drone systems rely on navigation and control algorithms to determine how to safely and efficiently operate in various environments. Within drone systems, classical control algorithms have included the use of proportional-integral-derivative control or simply PID control. PID control systems adjust the drone's position and orientation in space in a closed-loop fashion by defining a set position (target position or angle) and iteratively correcting current positional errors until the drone reaches the set position. While PID control systems are uncomplicated and require minimal processing power, they are unable to control systems in complex or dynamic multi-variable environments [21]. In response to these challenges, control systems based on artificial intelligence prove more adaptive. Using machine learning, AI systems predict drone behaviors for autonomous path planning and obstacle avoidance. Control deep learning algorithms predict and adjust critical flight parameters in real time [22, 33]. For dynamic environments, reinforcement learning algorithms are integrated, enabling the drone to self-determine and optimize real-time control parameters based on a set performance criterion. This approach of using machine learning for real-time performance adjustment allows a drone to optimize its control parameters in response to a changing environment [23].

As an illustration, in dynamic environments with moving obstacles, RL-based controllers can allow drones to shift their trajectories to avoid collisions autonomously. Another AI-based method is model predictive control (MPC), which leverages a model of the drone's dynamics to forecast future states, then optimizes control actions within a finite time period [24]. MPC is capable of resource management, such as obstacle avoidance, but due to high computational demands, it is difficult to implement universally across all resources [25].

Even though the state of the data lingers within the described framework thus generates questions of cut off dates for algorithms. They most definitely are flexible and adaptable. Algorithms have the challenge of being embedded. AI algorithms have great potential as control systems [26, 35]. They fall within the corners of restrained traditional control within the specified areas. Comparably AI-Navigation as well as control within complex environments under the described circumstances remains unrivaled.

D. Challenges in Autonomous Drone Navigation

The development of fully autonomous systems is challenged by several factors. In the case of autonomous drones, the complexity of real-time decision-making systems is of particular importance. The systems must interpret various streams of real-time sensor data, including photographs, LiDAR distance measurements, and IMU motion data [27, 32]. In dynamic environments, data must be processed quickly to allow timely decision making; otherwise, the system will experience a lag, navigation of the environment will be suboptimal, and the drone may collide with the environment. Inaccurate and unreliable navigation sensors will also impair system performance. For instance, low-light environments may cause cameras to fail, cluttered environments may cause LiDAR sensors to underperform, and IMUs may drift, making position and orientation of the drone overly inaccurate. Sensor fusion mathematically and statistically addresses some of these issues, yet additional sensor data increases system computational complexity. Autonomous navigation is also inhibited by the need for large computational resources, especially for deep learning and reinforcement learning systems.

E. Applications of AI-Driven Drone Systems

Across multiple industries, AI-powered drones have become versatile tools. In farming, AI drones assess soil conditions, apply fertilizers or pesticides, and lightweight drones perform autonomous crop health assessments thereby stimulating the economic efficiency of farming practices. AI algorithms facilitate farmers' targeting action through pest infestation and nutrient deficiency aerial image analysis. In search-and-rescue, AI drones perform aerial surveillance in disaster areas, assist in locating survivors, and offer real-time situational awareness. Such drones traverse challenging environments and utilize thermal vision and AI object detection to locate survivors and circumvent obstacles [28]. AI aids in autonomous navigation of GPS-equipped drones in GPS deprived areas like indoors or underground. In the commercial sector, Amazon and Google use AI to optimize drone's delivery routes, assess obstacles, reduce flight time, and energy use giving parcels. AI further enhances drone operational safety by identifying potential risks and autonomously avoiding safe routes.

AI AND CONTROL ALGORITHM DEVELOPMENT

A. Control Algorithms

Control algorithms guide and stabilize autonomous drones as they navigate different surroundings. These algorithms use the data received from the drones' various sensors and adjust the drones' positions, speeds and trajectories to achieve the desired flight parameters.

i. Classical Control Methods

In drone navigation, proportional-integral-derivative (PID) controllers are some of the most commonly used classical control algorithms. The controllers modify the drone's pitch, roll, and yaw in order to reduce the error to the desired state in terms of position and/or orientation. The proportional component deals with the current error, the integral component deals with errors from the past, while the derivative component predicts the error to come, based on the rate of change of the error. The computational simplicity of the PID controller offers ease of use, though for most drones, it is sufficient just for basic stabilisation and control of altitude. Still, PID controllers may lower the system performance in instances of complex and dynamic environments in which the boundaries are rapidly changing, and entail passive control [29]. Linear Quadratic Regulators (LQR) are another example of classical control algorithms for autonomous drone navigation. Operating as an optimal control method, LQR derives control inputs from the minimisation of a cost function, which encompasses both system state (e.g. position, velocity) and control (e.g. motor speed) exertion variables. Thus, in some instances, it outperforms PID, particularly in complex systems with multiple control inputs and interdependent control parameters.

ii. AI-Based Control Methods

The need for AI-enabled control techniques is necessary for the use of drones in more complicated scenarios. AI control employs neural networks as they can learn complicated features in the data. After training a neural networks with control policies for a drone, it can learn to adapt to shifting environments and use real time data to make rational decisions. Deep reinforcement learning (DRL) is a method used to guide drones in making real time decisions on route planning and obstacle avoidance. Drones learn to adapt and make behavioral changes as they engage with different terrains. Another AI control technique is model predictive control (MPC), in which a controller uses a drone's dynamics to create future drone state predictions and formulate control-optimization- drone commands for a limited predictive time horizon. Dynamic obstacle avoidance and work drone constraint, such as restricted distance to obstacle while constantly minimizing energy expenditure, MP control drones calculates and solves control functions on the command inputs. MP control is more advanced and effective than classical techniques but, it loses performance in predictive embedded systems. Real-time execution in embedded systems requires a lot of embedded systems in predictive MPC drones [30, 31].

B. AI Model Training

Training AI models for drone navigation involves several stages, including data collection, preprocessing, and model selection. The data used for training AI models must capture the nuances of the drone's environment to ensure the system can make accurate predictions and decisions in real-time.

i. Data Collection and Preprocessing

Data collection is the first stage in the training process of AI. With drones, this implies the collection of data from cameras, LiDAR sensors, IMUs, and different instruments mounted on drones. For instance, cameras, along with the other sensors, collect images that assist in visual navigation and in detecting obstacles. For final models to be functionally robust, data collection must capture varying environmental, lighting, and dynamically changing obstacle conditions. In addition to IMU sensors, which record and transmit position, velocity, and attitude information, and thus help in model training, will be particularly useful in situations when fusion of different models is performed. Image data preprocessing involves manipulations that systematically change images to enhance, normalize, and augment images through rotation, scaling, and other color adjustments to make the model robust to environmental variations. For the sensor data, techniques such as low-pass and high-pass filtering helps in noise reduction and to smoothen data. In the indexes, data marking and labeling is also major preparatory work. For object detection problems, images must have annotations indicate obstacle locations that must be avoided. This structured training helps the neural network learn to identify obstacles.

ii. Model Selection

Subsequent to data collection and preprocessing, model selection is the next step. Convolutional neural networks (CNNs) vastly outperform other options for visual navigation and obstacle detection. Designed to hierarchically learn the spatial structures of and relations within images, CNNs excel at object detection and classification. Static and dynamic obstacles (pedestrians and vehicles) can all be trained as targets for CNNs for obstacle avoidance. For the decision-making component of the tasks, that is controlling the drones, reinforcement learning (RL) is the most common approach. A drone can learn optimal control policies through trial and error and dynamically refine a decision-making process to adapt to new challenges. As a result of feedback through rewards and punishments, RL is also described as teach game and move pattern. Deep Reinforcement Learning (DRL) is one of the most taxing applications of neural networks, as it combines deep learning with RL, and allows for real-time complex decision making with minimal input. Path planning and dynamic obstacle avoidance are advanced tasks that drones can learn to perform with DRL. A deep neural network can manage a decision-making process through high-dimensional sensory input and provide feedback that is safe and efficient for real-time operation.

C. Path Planning and Obstacle Avoidance

For autonomous drone navigation, path planning and the avoidance of obstacles are critical components. While path planning identifies the best possible route the drone should take from its current position to the desired destination. However, avoidance of obstacles and safe navigation in dynamically changing environments are an integral part of drone navigation.

i. Development of Path Planning Algorithms

Autonomous drone systems utilize pathfinding methods like the A (A-STAR) * algorithm and Rapidly-Exploring Random Trees (RRT). A* identifies the shortest path from the starting point to the destination, all while avoiding obstacles by assessing the cost required to reach the target and merging the current cost with an estimated remaining cost and distance. It excels in graphically representable environments like grids; constraints can be mapped out easily. However, A* is less suited to hyper dynamic environments where real-time changes in constraints occur. In contrast, RRT attends to pathfinding in continuous space and works superbly in intricate obstacle-dense environments as it incrementally constructs a goal-directed tree of possible routes. Because RRT can rapidly produce a satisfactory path, it is appropriate for application in real-time, though it does not guarantee pathfinding accuracy. However, RRT is easily transcend able by RRT* as it develops a more intricate environment for pathfinding and iterative refinement for optimal pathfinding.

ii. Integration of AI for Dynamic Obstacle Avoidance

The adoption of artificial intelligence models, more specifically deep reinforcement learning (DRL), within real-time dynamic decision making for systems of path planning and obstacle avoidance, is on the rise. When developing path planning for scenarios with moving obstacles, such as pedestrians or ditches, and other drones, the classical methods may fall short with their anticipation and adaptability to changes surrounding the de-vel-oping path. With DRL, the drone can learn how to circumvent obstacles as the decision-making process of DRL boosts the optimization process with every encounter. Obstacle avoidance and trajectory optimization are by no means trivial tasks. However, with sensor data and environment feedback, DRL models empower the drone to dynamically re-plan its DRL, thereby circumventing their obstacles and efficiently maintaining a safe trajectory. The drone must also avoid newly introduced obstacles. For instance, if a moving pedestrian crosses a drone's path, the drone must decide within milliseconds to divert or take evasive action. The integration of deep learning and reinforcement learning allows for autonomous decision-making to minimize the risk of collision and maximize flight efficiency.

D. Navigation and Localization Techniques

i. Sensor Fusion Techniques for Accurate Localization

Sensor fusion is the process of integrating numerous sensors to enhance the precision and dependability of localization. Extended Kalman Filter (EKF) is one of the prevalent techniques within navigation systems on drones wherein EKF is employed to combine estimates derived from IMU, GPS, and other sensors. As a recursive filter, the EKF's function is to predict the state of a given system (state over time, system being the drone) by merging disparate sensor estimates of position and velocity (position and velocity being the state of system) and eliminating noise, resulting in an estimate of higher precision than the separate sensors. Another technique for localization is simultaneous localization and mapping (SLAM) on drones, more specifically, where GPS signals are available. SLAM is the only option for drones to autonomously construct a map of an unknown area while simultaneously keeping track of where the drone is in the map. This is critical for navigation in locations such as indoors or underground, where GPS signals are often severely attenuated or absent. Nonetheless, SLAM can be resource-hungry and is often not feasible for real-time applications without powerful computational devices.

ii. Real-Time Map Updating and Path Optimization Using AI

AI contributes to localization through real-time updates to maps and optimized pathways. A case in point is the use of drones powered by deep learning algorithms to discover and fix inaccuracies in environmental maps, refining the precision of maps. Moreover, AI assists in real-time core path optimization by detecting changes in the environment and adjusting the course in anticipation. Consider instances when an obstacle is predicted in the course of travel; the system will instantly compute and program an alternate path to guarantee a route that is safe and efficient.

E. System Implementation

i. Embedded AI Integration

Real-time autonomous navigation of drones closely depends on integrating AI into drones' embedded computing systems. Autonomy requires integration of trained AI models on the systems, including obstacle detection, path planning, and decision-making, allowing the drone to operate without external computing resources. For lightweight and energy-efficient embedded AI systems, considerable power for AI tasks and computing resources are needed, for example, specialized embedded platforms such as NVIDIA Jetson or Raspberry Pi. To ensure the platforms are used effectively without unnecessary power and memory consumption, embedded AI models need optimization for AI tasks to be performed rapidly and reliably. Critical to mission success and safety are the real-time execution and embedded AI systems' ability to adjust on-the-fly to sensor data. There the focus on AI execution speed is to use advanced optimization, including model pruning and quantization, and hardware acceleration, like GPU or FPGA. Since programming AI to run on embedded systems reduces latency, drones operated in real-time scenarios are more autonomous.

ii. Hardware-Software Interface

The convergence of hardware and software is crucial for the proper functioning of the drone's sensors and actuators in relation to the AI algorithms. IMU, GPS, camera and LiDAR and other hardware components need to be properly calibrated, integrated, and synchronized to the software control loop. In this way, the integrated system can analyze real-time sensor data and issue actuator commands (e.g., motors, gimbals) to alter the drone's flight. Real-time sensor integration demands efficient hardware and software communication.

RESULTS AND DISCUSSION

A. Experimental Setup

We present the results of the experimental testing and evaluation of the autonomous drone navigation system with embedded AI. The goal is to assess how well the system performs in various real-world scenarios and discuss the challenges faced during implementation.

i. Hardware Setup

Drone Platform: The DJI Phantom 4 quadcopter was used as the base platform due to its reliability, ease of integration, and the availability of additional control ports for modifying the system's capabilities.

Onboard Computer: The onboard computer used for running AI models was the NVIDIA Jetson Xavier NX. This platform was chosen for its high processing power, specifically for running deep learning models in real-time. The Xavier NX features an 8-core ARM CPU and 384 CUDA cores, which makes it ideal for edge AI tasks.

ii. Sensors

- LiDAR: The LiDAR-Lite v3 was used for depth sensing and generating 3D maps.
- RGB Camera: A Sony IMX219 camera was mounted on the drone to capture real-time images for obstacle detection and environment mapping.
- IMU: The drone was equipped with an InvenSense MPU-9250 IMU, which provided data about the drone's acceleration, orientation, and velocity.
- Ultrasonic Sensors: These were used to detect obstacles at short range, improving the system's ability to avoid collisions in confined spaces.
- Communication System: Communication between the drone and the control system was established via Wi-Fi for telemetry, while a Bluetooth connection was used for setup and maintenance.

iii. Software Setup

- AI Framework: TensorFlow Lite was used for the deployment of deep learning models, while OpenCV was employed for computer vision tasks like obstacle detection and object tracking.
- Control Algorithms: The drone's flight was controlled using a combination of PID controllers and Reinforcement Learning (RL). The PID controller was responsible for maintaining stability during flight, while RL was used for path planning and decision-making.
- Operating System: The onboard computer ran a custom version of Ubuntu 18.04 tailored to the NVIDIA Jetson platform. This OS supported all necessary libraries for real-time AI processing and sensor integration.

B. Evaluation of AI Models

In this section, we evaluate the performance of the AI models used for vision-based navigation, obstacle detection, and decision-making. These evaluations focus on the accuracy, robustness, and real-time processing capabilities of the models.

i. Model Overview

- Convolutional Neural Networks (CNNs): Used for image classification and obstacle detection tasks. The CNN model was trained to detect static and dynamic obstacles, such as walls, pedestrians, and moving vehicles.
- Reinforcement Learning (RL): Employed for path planning and decision-making. The RL algorithm was designed to allow the drone to navigate complex environments by learning from feedback provided by its actions.

ii. Model Performance

The CNN model performed well in object detection, but its performance was dependent on the image resolution, lighting, and the presence of dynamic obstructions. Conversely, the RL model achieved high success in dynamic decision-making but struggled with high-speed navigation due to the constrained processing capacity of the onboard AI.

Task	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing Time (ms)
Static Obstacle Detection	92	93	91	92	50
Dynamic Obstacle Detection	85	87	83	85	70
Object Tracking	90	88	92	90	60

Table 1: CNN Model Performance Evaluation

The performance of the CNN was evaluated through precision, recall, and F1-score, pertaining to both static and dynamic obstacles. The F1-scores of the model was 92% and 85% for static and dynamic obstacles respectively. This shows that the model was effective in controlled environments; however, improvements were needed for obstacles that were fast moving.

iii. RL Path Planning Performance

Advancements in path planning and decision-making have been seen in models employing reinforcement learning. An agent, in this case a drone, was trained using a reward system to avoid and navigate around obstacles, receiving rewards for successful avoidance and incurring penalties for collisions.

Task	Success Rate (%)	Average Path Length (m)	Average Collision Rate (%)	Training Time (hrs)
Indoor Navigation	95	35	3	30
Outdoor Navigation	93	50	4	45
Dynamic Obstacle Navigation	90	60	5	40

Table 2: RL Path Planning Performance

While the success rates for the RL model in both indoor and outdoor navigation are commendably high, the observed increase in collision rates remains concerning, especially in settings with fluid, dynamic obstacles. In terms of training, the RL model required between 30 to 45 hours, which was primarily dependent on the difficulty of the navigation tasks.

C. Performance Metrics

This section presents an analysis of the system's performance using key metrics such as flight stability, obstacle avoidance success rate, and computational efficiency.

i. Flight Stability

Flight stability was measured by evaluating the drone's ability to maintain steady flight while navigating through various environments. The stability metrics were derived from the drone's orientation data (pitch, roll, yaw) provided by the IMU.

Scenario	Pitch Stability (°)	Roll Stability (°)	Yaw Stability (°)	Max Drift (m)	Battery Consumption (Wh)
Indoor Navigation	±1.5	±1.5	±1.0	0.4	10
Outdoor Navigation	±2.0	±2.0	±1.5	1.0	15
Autonomous Landing	±1.0	±1.0	±1.0	0.3	8

Table 3: Flight Stability Metrics

The drone exhibited excellent stability during both indoor and outdoor navigation, with minimal drift. The autonomous landing scenario showed precise control, with the drone landing within a 0.3-meter range of the target.

ii. Obstacle Avoidance

Different scenarios were introduced in the environment, both static and dynamic, for the obstacle avoidance system testing phase. Multiple scenarios were created for system evaluation based on different metrics. The system's success rate in avoiding collisions permeated each scenario as the only evaluation metric.

Environment	Detection Accuracy (%)	Avoidance Success Rate (%)	Average Processing Time (ms)
Indoor (Static)	92	95	100
Outdoor (Dynamic)	85	88	150

Table 4: Obstacle Avoidance Performance

The obstacle detection system managed to avoid static obstacles with great precision. Yet, the introduction of dynamic obstacles resulted in a slight decrease in the success rate for avoidance, illustrating system dependency on environmental considerations such as sensor performance and processing duration.

iii. Computational Efficiency

Real-time performance was essential for the system, especially during flight. Processing times were recorded for tasks like image classification, obstacle detection, and path planning.

Task	Processing Time (ms)	GPU Utilization (%)	CPU Utilization (%)
Image Classification	45	70	30
Obstacle Detection	80	85	55
Path Planning	150	65	45

Table 5: Computational Performance

The system achieved acceptable real-time processing speeds for image classification and obstacle detection, but path planning tasks took longer, especially in dynamic environments.

D. Comparison with Existing Solutions

To benchmark the performance of the developed system, a comparison was made with other commercially available autonomous drones such as Skydio 2 and Parrot Anafi USA.

i. Comparative Performance

Feature	Our System	Skydio 2	Parrot Anafi USA
Obstacle Detection Accuracy	92%	85%	88%
Path Planning Efficiency	95%	90%	85%
Battery Life (min)	20	30	25
Cost (USD)	1500	2500	1900

Table 6: Comparative Performance of Drones

Particularly in the indoor settings, our system demonstrated superior obstacle detection accuracy and path planning efficiency compared to the Skydio 2, despite having somewhat lower battery life, which suggests a possible trade-off in performance and battery consumption.

E. Limitations and Challenges

i. Computational Constraints

Despite the powerful capabilities of the NVIDIA Jetson Xavier NX, the onboard system faced limitations when processing complex AI models in real-time, particularly during high-speed flight.

ii. Sensor Accuracy

The reliance on visual sensors for obstacle detection led to challenges in environments with poor lighting or rapidly changing conditions. Future improvements in multi-sensor fusion are needed to address these issues.

iii. Real-Time Decision-Making

The reinforcement learning algorithm showed significant promise but required more optimization to handle decision-making in real-time without lag, especially in fast-moving environments.

CONCLUSION

The design, development, and evaluation of embedded AI based autonomous navigation systems for AI integrated autonomous drones is an important milestone in robotics and AI. Drone autonomous navigation in complex environments became possible by embedding AI systems with real-time flight control algorithms. Using embedded AI systems with NVIDIA Jetson Xavier NX AI powered embedded systems and deep learning models for obstacle detection, path planning, and real-time decision making is used. Evaluation in a variety of scenarios such as indoor navigation, outdoor navigation and dynamic obstacle avoidance showed outstanding performance of the system. The implementation showed some challenges such as the need for more efficient real-time decision making and other computational challenges. Advanced system capabilities relating to flight stability, path optimization, and obstacle avoidance defied the challenges. Challenges pertaining to system capabilities such as dynamic decision making and real time system computing showed the need to develop navigation systems for more complex, autonomous drones.

Research in autonomous navigation and artificial intelligence integrated within drone systems pioneering. Among the notable advancements includes training deep learning models on embedded systems for real-time autonomous flight control. This allows drones to make rational decisions and navigate multifaceted terrain without human assistance. Furthermore, the novel implementation of reinforcement learning to dynamic path planning and decision-making allows drones to alter course autonomously within shifting environmental parameters. The integration of artificial intelligence models for visual recognition and sensor fusion techniques profoundly advances real-time situational understanding. This enhances a drone’s ability to function in diverse environments.

In the future, there will undoubtedly be many opportunities to expand the capabilities of the system. One of the most important potential advancements involves the optimization of AI models, which will be a requirement for greater system speeds and more complex task real-time decision-making. Advances in reinforcement learning and deep learning may offer drones the ability to take on more difficult tasks like low-light navigation and the more troubling and dynamic obstacles. Battery optimization is critical, as the system will benefit from un-tethered longer missions. Other AI applications to be embedded in drone systems like swarm robotics and multi-agent systems, will be game changers in thousands of industries, including, but not limited to, agriculture, search-and-rescue missions, and environmental monitoring. Such advancements will improve the capabilities of the drones themselves, but will also enable highly complex coordinating tasks to be performed in large numbers. This research serves as a springboard to the more complex and numerous autonomous drones equipped with AI and the myriad of uses in diverse fields and industries that will follow.

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