An AI-Powered Aerial Navigation System for Dynamic Accessibility Aware Pathfinding

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***Abstract*—Navigating indoor environments brings significant challenges for individuals with mobility impairments, such as wheelchair users, older adults, those with temporary injuries, and others requiring accessible pathways. A key barrier is the absence of reliable, real-time information about indoor layouts, accessibility features, and temporary obstacles. Existing navigation solutions often rely on static maps and outdated data, limiting their ability to address the dynamic and specific needs of users seeking accessible routes. To overcome these limitations, this study introduces an Artificial Intelligence (AI)-assisted drone-based navigation system that provides real-time guidance and adaptive support for individuals with mobility restrictions. We developed and integrated a custom object detection model into the aerial platform to identify accessibility features and environmental obstacles. In addition, a dynamic path-planning algorithm enables the drone to autonomously guide users through accessible routes, adjusting in real-time to environmental changes. The system reroutes users when unexpected obstructions arise, ensuring uninterrupted and reliable navigation to the targeted destination. We evaluated the system's performance through experiments in a controlled environment, demonstrating its effectiveness and potential for real-world applications.**

Keywords-Unmanned Aerial Vehicles; Drone-as-a-Service; Artificial Intelligence; Accessibility; Mobility Impairment.

I. Introduction

Navigating indoor environments poses challenges for many individuals; however, these difficulties are significantly intensified for those with mobility impairments, including wheelchair users, the elderly, and others requiring accessible pathways. Unlike outdoor environments, which might benefit from widely adopted GPS-based navigation systems, indoor spaces, such as office buildings, shopping malls, hospitals, and airports, are often complex, dynamic, and poorly documented. People with mobility limitations face barriers such as stairs, narrow corridors, inconveniently placed ramps, surface defects, and obstacles that change frequently due to construction, furniture rearrangements, or crowded conditions. They often have to rely on pre-researched maps, verbal directions, or external assistance. In emergencies, timely access to accessible paths can be critical, yet existing systems rarely provide the real-time guidance needed to navigate these spaces safely.

Although considerable progress has been made in accessibility-aware tools and standards for outdoor navigation, indoor environments remain largely unsupported in terms of real-time navigational assistance. People with disabilities often encounter inaccurate, outdated, or difficult-to-access information about accessible paths, ramps, elevators, and temporary obstructions. The cognitive load required to process such information adds to the stress of independent navigation, creating a substantial barrier to mobility, autonomy, and inclusion.

Tools like Google Maps' Accessible Places feature provide high-level accessibility data, but lack support for dynamic rerouting or detection of temporary obstacles. These gaps intensify the urgent need for solutions that can provide adaptive, real-time indoor navigation responsive to users' accessibility requirements.

Recent advances in robotics and Artificial Intelligence (AI) offer promising paths for addressing aforementioned challenges. Unmanned Aerial Vehicles (UAVs), commonly known as drones, have demonstrated broad utility in domains, such as agriculture, surveillance, emergency response, and delivery services. Integrating drones with computer vision and deep learning can enable real-time detection of environmental features and obstacles, while also supporting dynamic path planning. This capability is particularly relevant for indoor environments, where static maps are insufficient, and routes may need continuous updating in response to environmental changes.

Despite these advances, most existing drone-based or AI-assisted navigation systems focus on outdoor applications or visually impaired users, leaving a critical gap for mobility-impaired populations in indoor spaces. There is a need for systems that combine accessibility-aware planning, real-time perception, and reliable guidance to ensure users can navigate complex indoor environments independently or with minimum of help.

In this study, we present a novel AI-assisted drone-based navigation system designed specifically for real-time operation in dynamic indoor environments. Our platform combines a custom object detection model, capable of recognizing accessibility features and obstacles, with a real-time path planning algorithm that prioritizes accessible and safe routing. Unlike previous approaches that rely on pre-recorded routes or static maps, our system continuously adapts its path in response to environmental changes, offering an adaptive navigation experience. The contributions of this paper is as follows:

1. **A practical architecture for drone-assisted indoor navigation** that supports real-time accessibility-aware

guidance.

2. **Integration of AI-based object detection with dynamic path planning** to identify and respond to temporary obstacles, changing layouts, and accessibility features.
3. **Experimental evaluation in controlled indoor environments** demonstrating feasibility and potential to improve independent mobility.
4. **A roadmap for future enhancements**, including dataset and training improvements, integration of crowdsourced annotations, and broader validation across varied indoor environments.

By advancing the convergence of AI, robotics, and accessibility, our system introduces a novel and adaptable solution to a longstanding problem in inclusive navigation. It demonstrates the potential of drones to serve as mobile, intelligent guides, ensuring safe, accessible, and efficient indoor mobility for individuals with physical disabilities.

This paper is structured as follows: Section II reviews related work on accessibilty systems, path navigation, and drone-assisted guidance. Section III introduces the overall system architecture. Section IV, describes the object detection process, including the algorithm, the steps used to identify accessibility features and obstacles, and the corresponding performance results. Section V presents our dynamic path navigation algorithm, which guides users along accessible routes by using real-time environmental data, followed by an anlysis of its complexity and completeness. Finally, Section VI summarizes the contributions and outlines directions for future work.

II. Related Work

A wide body of research emphasizes the limitations of current systems in addressing the needs of people with disabilities indoors. Studies have documented the challenges faced by blind users, including poor signage and misaligned digital-physical information [1], as well as the cognitive load involved in navigating unfamiliar spaces [2]. Other work has examined mobile applications and assistive technologies for people with visual or cognitive impairments [3][4]. However, relatively little attention has been given to real-time, assistive indoor navigation for those with mobility-related impairments. The work [5] on mobile indoor navigation assistance for mobility impaired people proposes a smartphone-based system using Wi-Fi localization and pre-mapped accessibility data to guide users indoors, focusing on using accessible maps and wireless sensor positioning to guide users through complex indoor spaces. While effective for static environments, it lacks dynamic perception and real-time path adaptation. Rafful et al. [6] describes the role of simulation frameworks in assessing indoor accessibility for people with disabilities. While such tools are valuable for design-time evaluation, they do not provide in-the-moment guidance for users moving through an indoor environment. As a result, People With Mobility Disabilities (PWMD) are often left without timely information when routes become blocked or when layouts change.

Issues, such as misalignment between maps and real-world landmarks, uneven terrain, inaccessible detours, and poorly placed signage make independent travel difficult. These obstacles are further worsened by the mental effort required to process complex way-finding information, often turning navigation into a stressful and unreliable task. In emergencies, the situation becomes even more critical, as the absence of real-time navigation support can lead to dangerous delays and confusion. Studies like [7][8] demonstrate the limitations of static maps or pre-fed navigation systems, which often fail to provide the real-time updates needed to address dynamic changes in the environment, such as construction work, temporary obstacles, or crowded areas. Moreover, people with disabilities may hesitate to disclose their conditions or seek assistance, further emphasizing the need for inclusive and adaptive technological solutions.

Some researchers have explored computer vision and deep learning for assistive navigation. For example, Nasralla et al. [9] recommend that researchers use deep learning and machine vision for hazard detection, offering audio or tactile feedback to assist visually impaired users. Khemmar et al. [10] emphasize the potential of deep learning algorithms for robust pedestrian detection and target tracking in dynamic settings. While promising, these solutions focus primarily on outdoor environments or visually impaired users, leaving gaps in addressing indoor navigation for people with mobility impairments.

One promising but underexplored path is the use of drones for indoor navigation. Their proven effectiveness in infrastructure inspection, environmental monitoring, and emergency response indicates their potential to support accessibility-focused applications. The introduction of commercial services like Amazon's drone delivery [11] has fueled public interest and innovation in the field. With the global drone market projected to grow from \$15.9 billion in 2023 to \$53.4 billion by 2030 [12], the supporting technologies for real-time indoor drone navigation, such as object detection and obstacle avoidance, are increasingly accessible.

Recent studies have explored drones as guides or assistive agents for people with disabilities. For instance, Avila et. al. [13] explore the use of drones to assist visually impaired individuals in navigating public spaces, relying on auditory cues and airflow produced by the drones. The drones follow pre-recorded paths mapped by a sighted individual. Iuga et al. [14] combine wearable fall detectors with drone-based response systems for emergency scenarios. Their system features a fall detection device, worn on the upper arm, which monitors heart rate and detects falls. Upon detecting a fall, the system autonomously dispatches a UAV carrying a first aid package to the patient's location, with the UAV's route planned through a smartphone-based application at an emergency call center. In [15], the authors propose a system that integrates Virtual Reality (VR) with drones to deliver engaging visual experiences for individuals with limited mobility. By streaming live video from the drone's onboard camera to the VR headset, users can experience remote environments in real-time, effectively bringing the outside world to those unable to physically explore it. While these applications are innovative, they do not directly address real-time indoor navigation for individuals with mobility impairments.

Our work introduces a novel drone-based navigation system designed to assist people with mobility impairments in real-time, dynamic indoor environments. Unlike approaches that rely on pre-recorded routes or fixed maps, our system suggests active detection of key features of the environment, including ramps, stairs, elevators, and obstacles, and continuously updates its planned route as conditions change. The platform integrates an object detection model to identify accessibility features and obstacles in real time, with a real-time path planning algorithm that selects accessible and safe routes for the user. This combination enables the drone to act as a dynamic guide, leading users through the environment while responding to layout changes, temporary obstructions, or changing accessibility conditions.

Effective path planning is critical for any navigation system, particularly for assistive technologies utilizing drones. Research on safety-focused path planning and genetic algorithm-based approaches provide insights into optimal route selection and efficiency [16][17]. In [16], Castelli et al. concentrate on the importance of incorporating safety metrics to enhance reliability during UAV missions. Their method prioritizes minimizing risk by accounting for potential hazards in the operating area, particularly suited for outdoor environments, such as urban areas or disaster zones, where UAVs face dynamic, unpredictable conditions. The study discusses the importance of incorporating safety metrics to enhance reliability during UAV missions. Wang et al. introduced a path-planning method based on genetic algorithms, focusing on outdoor UAV applications [17]. The study is tailored for scenarios requiring efficient and adaptive route selection, such as search and rescue operations, environmental monitoring, and agricultural surveying. This method uses evolutionary computation to optimize UAV paths with multiple objectives, including minimizing energy consumption, avoiding obstacles, and reducing flight time. Genetic algorithms iteratively refine candidate paths, balancing trade-offs between efficiency and safety. Although these approaches demonstrate robust path planning in general settings, they are not designed with accessibility in mind. Our contribution lies in designing a path planning algorithm while prioritizing accessible features and user needs, enabling drones to serve as mobile assistive agents within real-world indoor spaces.

In this article, we address a critical and underexplored gap at the intersection of artificial intelligence, accessibility, and robotics. By integrating real-time object detection and accessibility-aware path planning into a Drone-as-a-Service (DaaS) platform, we aim to support independent mobility of people with physical disabilities in indoor environments that are often inaccessible, unpredictable, or hazardous. Our system offers an adaptable, intelligent, and practical solution to a longstanding problem in inclusive navigation technology. Although the primary focus of this work is not on drone safety concerns, such as the risk of drones falling onto individuals, we acknowledge this as an important practical consideration. One straightforward mitigation strategy involves installing a transparent, glass-like barrier or protective netting below the ceiling, allowing drones to operate above it. This architectural modification effectively eliminates the risk of falling objects and can be readily implemented in public buildings. Furthermore, drone charging and docking stations can be integrated above this barrier to support reliable and safe operations.

III. System Architecture

To support accessibility-focused indoor navigation, the proposed system utilizes an AI-enabled drone that guides users along safe and accessible paths while dynamically adapting to changing environmental conditions. The overall architecture is illustrated in Figure 1. At the core of the system is the educational RoboMaster Tello Talent drone, developed by DJI [18]. This compact, lightweight platform (∼90 g) is equipped with a built-in camera and supports programmable control through a Software Development Kit (SDK). The drone communicates wirelessly with a Ground Control System (GCS) over a Wi-Fi network using the User Datagram Protocol (UDP). Live video streams captured by the drone are transmitted to the GCS, where they are processed by the object detection algorithm. Based on this analysis, the GCS issues navigation commands to the drone, enabling it to guide users reliably toward their intended destinations.

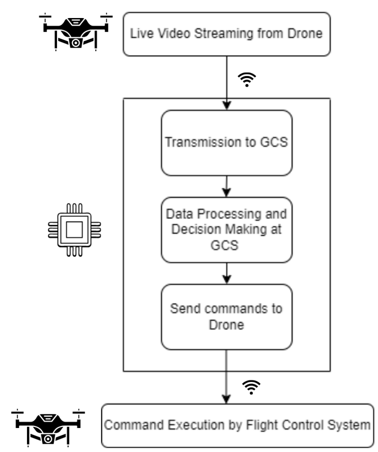

Figure 1. System architecture of the proposed drone-based navigation system, illustrating the drone, wireless communication with the GCS, real-time object detection, and navigation command feedback for guiding users along accessible routes.

While the long-term objective is to achieve fully onboard processing for autonomous navigation on capable drones, the current implementation strategically uses edge computing to support real-time decision-making in controlled environments. This approach allows us to utilize educational drones while still performing computationally intensive tasks, such as object detection and path planning, with accuracy and efficiency. By offloading these processes to a GCS, we demonstrate the feasibility and effectiveness of our method, establishing

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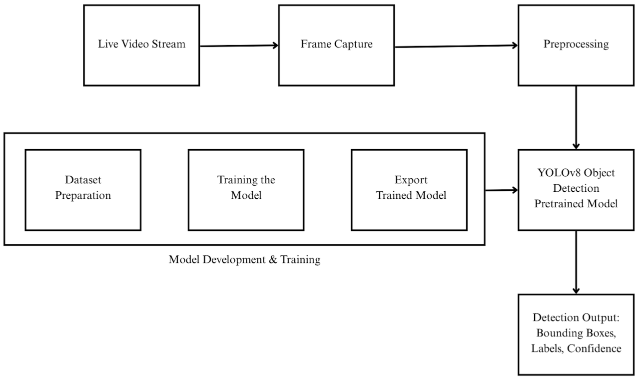

Figure 2. Workflow of the YOLO object detection pipeline used in the proposed drone-based navigation system. The GCS receives live video streams from the drone and processes each frame using the pre-trained YOLO model [20].

a strong foundation for future deployment on more advanced platforms.

IV. Accessibility-Oriented Object Detection using Drones

In this section, we focus on the object detection procedure. A key component in developing a real-time *Drone Accessibility Assistant* for individuals with mobility impairments is the implementation of an efficient object detection algorithm. For this purpose, You Only Look Once (YOLO) [19] was selected due to its high speed and accuracy. YOLO formulates object detection as a single-stage regression problem, eliminating the complexity and latency of traditional multi-stage pipelines.

Figure 2 illustrates the YOLO workflow, beginning with live video capture from the drone and continuing through frame preprocessing, dataset preparation, model training, and export. The trained model is then deployed for YOLOv8-based object detection, which generates bounding boxes, labels, and confidence scores. The ground control station receives the live video streams and processes each frame using the pre-trained YOLO model [20]. To enable rapid prototyping and efficient training, we used Google Colab as the development platform, utilizing its cloud-based resources to accelerate model training and improve inference performance.

A dataset consisting of over 4,500 images was collected from various sources, including [21][22][23]. The distribution of image categories is illustrated in Figure 3. The top-left bar chart shows the number of instances for each class: accessibility symbol, person, potholes, ramps, and stairs. The top-right plot overlays all bounding boxes to visualize their spatial coverage. The bottom heatmaps represent the distribution of bounding box center coordinates (x, y) and their width–height dimensions across the dataset. Each image was manually annotated to identify regions of interest corresponding to target objects relevant to accessibility, such as stairs, ramps, and potholes.

The YOLOv8-medium model from the Ultralytics library [24] was trained for 60 epochs with an input size of 640 pixels in a Google Colab environment. Model performance

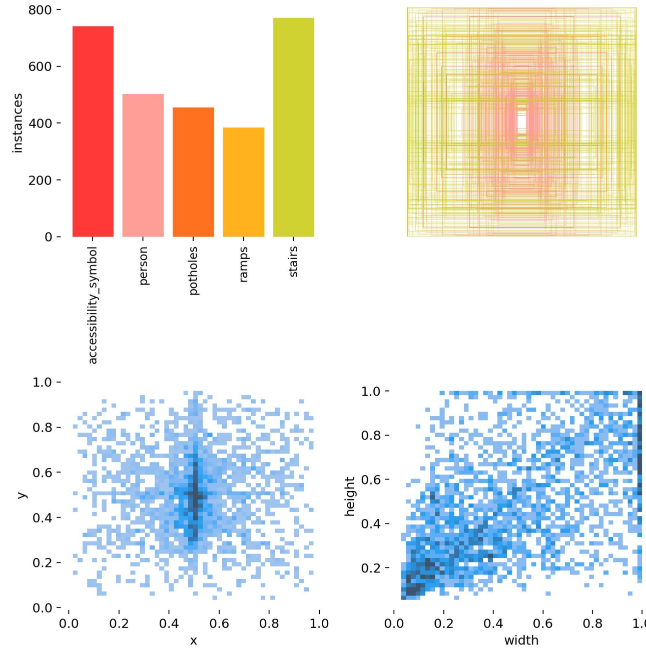

Figure 3. Dataset visualization for accessibility object detection. Top-left: class distribution; top-right: bounding box overlay; bottom-left: bounding box centers; bottom-right: bounding box dimensions.

was evaluated using precision, recall, and mean average precision (mAP) on a validation set. Final predictions on the test set were generated with a confidence threshold of 0.5.

The object detection model demonstrated good performance, achieving a mean average precision (mAP) of 80% at an Intersection over Union (IoU) threshold of 0.5. As illustrated in the confusion matrix (Figure 4), the model indicates robust capability in acurately identifying instances of accessibility symbols (93%) and stairs (90%), with moderate performance on ramps (85%), potholes (73%), and persons (70%). An important area requiring improvement is the model's handling of the background class. As illustrated in the confusion matrix, multiple true instances from other object classes, such as person and potholes, were misclassified as background. These false negatives suggest that the model occasionally fails to detect the presence of an object, instead attributing it to the background class, thus inflating background predictions. Conversely, there are cases where true background pixels were incorrectly classified as object classes, resulting in false positives. These misclassifications reflect a limitation in the model's ability to reliably differentiate between objects of interest and true background. To address this, we prioritize improving the quality of background annotations and increasing the representation of frequently confused background regions during training. These enhancements are crucial for boosting the model's overall precision and recall across all classes.

Figure 5 presents a series of plots illustrating the model's performance evolution over approximately 60 training epochs. These graphs provide critical insights into the learning process, convergence, and generalization capabilities of the model.

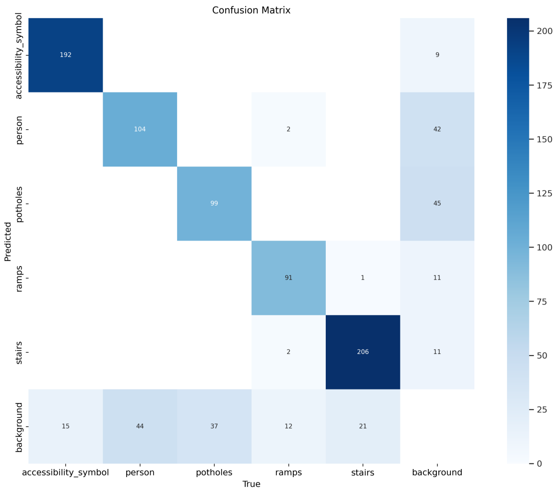

Figure 4. Confusion matrix illustrating the performance of the trained model across all classes. The diagonal values represent correctly classified instances, while the off-diagonal values indicate misclassifications between classes.

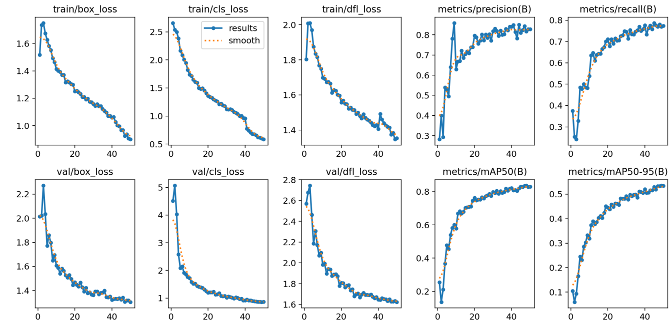

Figure 5. Training and validation performance of the YOLOv8 model across epochs, showing convergence through reduced loss and improved accuracy, demonstrating effective generalization to unseen data.

The top row of plots displays the training loss metrics. All three curves exhibit a consistent and continuous downward trend throughout the training epochs. This steady decrease in training loss indicates that the model is effectively learning from the training data and improving its ability to accurately localize objects (box loss), classify them correctly (classification loss), and refine its distribution focal loss.The smoothness of these curves suggests a stable training process, free from significant oscillations or divergence, which is indicative of appropriate hyperparameter selection and model architecture.

The bottom row of plots details the validation loss metrics and key performance indicators. Similar to the training losses, the validation loss curves demonstrate a steady decline, eventually stabilizing towards the latter epochs. This crucial observation indicates that the model is generalizing well to unseen data, effectively avoiding overfitting to the training set. The continuous improvement in validation performance reinforces the model's robustness and its capacity for real-world application.

Furthermore, the performance metrics showcase significant progress over time. Both *metrics/precision(B)* and *metrics/recall(B)* exhibit a strong upward trajectory, stabilizing at high values by the end of training. This suggests that the model is becoming both more selective, making fewer false positive predictions, and more comprehensive in identifying true positives. The mean average precision metrics offer a more comprehensive assessment of detection performance. In particular, *metrics/mAP50(B)*, evaluated at an IoU threshold of 0.50, shows rapid and sustained improvement, achieving a high score confirming the model's effectiveness in identifying objects with moderate overlap. More critically, *metrics/mAP50-95(B)*, which averages performance across IoU thresholds from 0.50 to 0.95, also exhibits steady gain. Although this metric naturally yields lower values due to stricter localization requirements, its continuous upward trend signifies the model's increasing accuracy in both object detection and localization. The continued rise of this metric suggests that additional training epochs could further refine bounding box precision and overall model performance.

In summary, the combined analysis of the confusion matrix and the training/validation metrics demonstrates the strong performance of the developed model. The confusion matrix reveals high true positive rates across key target object classes, while also identifying the background class as a primary source of misclassifications. This presents an area for targeted refinement, specifically, improving the model's ability to distinguish between actual objects and true background. Concurrently, the training and validation curves demonstrate the model's effective learning and successful generalization, with consistent improvement in all key performance indicators, including precision, recall, and mean average precision.

While publicly available data sources provided a practical basis for developing and evaluating our models, we acknowledge potential domain inconsistencies and inherent dataset biases. Future work will focus on improving dataset relevance and reducing biases, for example by collecting additional domain-specific images or incorporating crowdsourced annotations. We also plan to address class imbalance through data augmentation and sampling strategies. Beyond data considerations, we aim to to enhance detection performance through hyperparameter tuning and advanced training strategies, particularly for underperforming classes. Addressing background-related confusion through methods, such as data augmentation, improved annotation quality, hard negative mining, or context-aware object detection offers a promising direction for improving the model's accuracy and real-world robustness.

V. Dynamic Path Navigation Algorithm

In alignment with our system design objectives, we developed a *Dynamic Path Navigation Algorithm* to enhance drone's autonomous navigation capabilities through real-time environmental perception and adaptive decision-making in dynamic indoor environments. Central to the system is the drone's ability to autonomously scan its surroundings, detect obstacles, and dynamically determine an alternative route, thereby ensuring efficient and safe path navigation.

Algorithm 1 Dynamic Path Navigation Algorithm for Autonomous Drone Guidance

procedure GRAPHCONSTRUCTION
  Construct accessibility-compliant graph $G = (V, E)$
  return G
procedure HANDLEOBSTACLE(G, current_node, next_node, destination)
  RemoveEdge(G, current_node, next_node)
  $P \leftarrow$ Dijkstra(current_node, destination)
  return P
procedure NAVIGATE(source, destination)
  G $\leftarrow$ GraphConstruction()
  current_node $\leftarrow$ source
  $P \leftarrow$ Dijkstra(current_node, destination)
  while current_node $\neq$ destination **do**
    next_node $\leftarrow$ NextNode(P)
    if ObstacleDetected(current_node, next_node) **then**
      $P \leftarrow$ HandleObstacle(G, current_node, next_node, destination)
    else
      current_node $\leftarrow$ next_node
  Display "Arrived at Destination"

We assume the availability of prior information about the premises, such as an initial floor map of the building, to construct a graph-based representation of the navigable environment. Specifically, the environment is modeled as a directed graph $G = (V, E)$, where vertices V represent key decision points from which the drone can move in various directions (e.g., intersections, turns, or locations of interest), and edges E denote traversable connections between them. Each edge carries a weight reflecting the cost or distance of traversal.

This graph serves as the operational blueprint for path planning. Given a source node and a destination node, the algorithm computes an optimal route using Dijkstra's algorithm. As the drone follows the computed path, it continuously monitors the environment to detec and respond to unexpected obstacles in real time. If an obstruction is detected along the next segment of the planned path, the algorithm dynamically updates the graph by removing the blocked edge and recalculating an alternative shortest path from the current node to the destination. The process iterates until the drone reaches the destination node, at which point it signals successful arrival.

Algorithm 1 provides a detailed step-by-step description of this adaptive path-planning framework, which integrates classical graph-based planning with real-time environmental perception to enable reliable, obstacle-aware navigation in dynamic indoor settings.

In the following, we first analyze the algorithm's worst-case time complexity, providing insight into its computational efficiency. We then present a discussion on its completeness, demonstrating that the algorithm is guaranteed to find a path if one exists in the graph.

Theorem 1. *The worst-case runtime of our Dynamic Path Navigation algorithm is $O(\mathcal{E} \cdot (|V| + |E|) log|V|)$ in the worst case.*

Proof. The overall time complexity of the Dynamic Path Navigation algorithm is driven by two primary operations: the computation of the shortest path using Dijkstra's algorithm and the real-time obstacle detection mechanism during path execution.

Initially, the algorithm computes the shortest path from the source to the destination node on a pre-constructed graph $G = (V, E)$, where V represents decision points and E denotes traversable edges. In the event of encountering unexpected obstacles during navigation, the algorithm dynamically removes the affected edge from the graph and recomputes the shortest path from the current node to the destination. Let $\mathcal{E}$ denote the total number of such path recalculations triggered by obstacle detections.

Using a priority queue implementation (e.g., binary heap), the time complexity of Dijkstra's algorithm for a single invocation is

$$O\left((|V| + |E|) \log |V|\right).$$

Therefore, across all $\mathcal{E} \leq |E|$ recomputations, the total cost of path planning becomes:

$$O\left(\mathcal{E} \cdot (|V| + |E|) \log |V|\right).$$

In addition, the drone performs a constant-time obstacle check while traversing each edge along the path. In the worst-case scenario, every edge in the graph may be evaluated at least once for obstacle presence, contributing an additional linear cost of $O(|E|)$ for real-time sensing and reaction.

Thus, the total worst-case time complexity of the navigation algorithm is:

$$O\left(\mathcal{E} \cdot (|V| + |E|) \log |V| + |E|\right).$$

This complexity reflects the integration of classical graph-based planning with adaptive, sensor-driven updates, enabling robust and responsive indoor navigation in dynamic environments. □

We now present the completeness guarantee of the proposed path navigation algorithm in Theorem 2. We assume that the drone initiates the algorithm at the source node s, with the objective of reaching the destination node d.

Theorem 2. *If there exists at least one unblocked path from the source node s to the destination d at any time during execution, then the Dynamic Path Navigation Algorithm will reach d in finite time.*

Proof. The algorithm begins by computing the shortest path from the current node to the destination node using Dijkstra's algorithm. Dijkstra's algorithm is complete and optimal for graphs with non-negative edge weights, and thus will return a valid path if one exists in the initial graph.

As the drone follows this path, it continuously monitors the immediate next edge for obstacles. If an obstacle is detected on edge (u, v), the edge is removed from the graph, and the algorithm recomputes the shortest path from the current node u to the destination d using Dijkstra's algorithm on the updated graph.

At each iteration, the graph becomes a subgraph of the original, with potentially fewer edges due to obstacle-induced removals. If a valid path exists from the current node to the destination in the updated graph, Dijkstra's algorithm will find it. The algorithm terminates either when the destination is reached or when no path exists in the current subgraph.

Consequently, as long as at least one unblocked path exists from the current node to the destination, the algorithm will eventually find and traverse it. Upon reaching d, the algorithm halts successfully, establishing completeness under this assumption.

□

VI. Conclusions and Future Work

This study introduces an innovative AI-assisted drone-based navigation system aimed at supporting individuals with mobility impairments as they navigate complex indoor environments. By integrating a customized object detection model with dynamic path planning, the system enables real-time identification of accessibility features and obstacles, allowing autonomous aerial robots to guide users along safe and accessible routes. Experimental evaluations conducted in a controlled setting demonstrate the system's feasibility and potential to address critical gaps left by traditional, static navigation tools. The findings showcase the critical role that aerial robotics can play in improving independent mobility, reducing navigational barriers, and advancing inclusion within built environments. The ability of the system to adaptively re-route users in response to environmental changes further reflects its applicability to real-world settings where accessibility needs are both pressing and variable. Future work may focus on improving the accuracy and adaptability of the object detection model to perform reliably across a variety of architectural settings. Refinements to the overall system design, encompassing both software and hardware components, combined with evaluations beyond controlled environments to account for real-world factors, such as lighting variability, human presence, ceiling obstructions, and operational safety, will strengthen scalability and reliability. Pilot deployments or simulation-based validations can further increase credibility and readiness for broader adoption.

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