TITLE: AI DRIVEN SMART NAVIGATION SYSTEM FOR GPS DENIED AREAS

ABSTRACT

Autonomous navigation in GPS-denied environ ments, such as tunnels, forests, and urban canyons, requires robust localization and obstacle avoidance without reliance on satellite signals. This paper presents a real-time navigation system that integrates data from an Inertial Measurement Unit (BNO085), magnetometer (HMC5883L), LiDAR, rotary encoder, and NoIR camera using a Raspberry Pi 5-based embedded platform. An Extended Kalman Filter (EKF) fuses multi-sensor data for accurate state estimation, while lightweight image pro cessing using YOLOv8 enhances obstacle detection. The system emphasizes computational efficiency to ensure low-latency per formance on resource-limited hardware. Experimental validation demonstrates reliable path planning, obstacle avoidance, and localization accuracy, highlighting its suitability for applications in robotics, defense, and search-and-rescue operations where GPS signals are unavailable.

Keywords — GPS-Denied Navigation, Sensor Fusion, Kalman Filter, Visual SLAM, Autonomous Navigation.

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LIST OF ABBREVIATIONS

ACRONYM		ABBREVIATION
GPS	-	Global Positioning System
IMU	-	Inertial Measurement Unit
EKF	-	Extended Kalman Filter
VO	-	Visual Odometry
UART	-	Universal Asynchronous Receiver-Transmitter
I2C	-	Inter-Integrated Circuit
GUI	-	Graphical User Interface
Wi-Fi	-	Wireless Fidelity
ROS	-	Robot Operating System
LiDAR	-	Light Detection and Ranging
INS	-	Inertial Navigation System
SLAM	-	Simultaneous Localization and Mapping
OL	-	Output Layer
FL	-	Fusion Layer
PL	-	Processing Layer
SL	-	Sensor Layer

CHAPTER 1

INTRODUCTION

1. OVERVIEW

Autonomous navigation has traditionally relied heavily on the Global Positioning System (GPS) to provide continuous, real-time positional awareness. GPS has enabled a wide range of applications, from mobile mapping and vehicle guidance to aerial drone operations and robotic automation. However, environments where GPS signals are unavailable, degraded, or deliberately denied pose significant challenges to autonomous systems.

This project addresses the urgent need for developing a robust navigation system capable of maintaining reliable localization without depending on GPS signals by integrating multi-sensor fusion and real-time image processing techniques.

2. IMPORTANCE

Navigation without GPS is essential for ensuring uninterrupted autonomy in a variety of critical applications. In tunnels, dense urban areas, forests, indoor environments, or during military operations where GPS jamming may occur, autonomous systems must continue to function reliably. A failure to navigate accurately in such environments can compromise mission success, operational efficiency, and human safety.

Thus, building a GPS-independent navigation system not only enhances operational reliability but also extends the reach and capability of autonomous platforms into new, challenging territories.

3. CHALLENGES

Operating in GPS-denied environments introduces several technical challenges:

- **Drift in Inertial Navigation:** Over time, small errors accumulate, causing significant position inaccuracies.
- **Environmental Variability:** Changing lighting, weather, or surroundings affect visual odometry.
- **Sensor Noise:** Low-cost IMUs and cameras are prone to noise and inaccuracies.
- **Computational Complexity:** Real-time processing of multi-sensor data demands efficient and lightweight algorithms.
- **Dynamic Obstacles:** Moving objects, changing terrains, and unstructured environments complicate path planning. Overcoming these issues requires a system that can intelligently combine multiple sensor inputs, correct errors dynamically, and operate efficiently in real time.

4. NEED FOR ALTERNATIVE

Since traditional GPS-based systems fail under the above conditions, there is a growing need for alternative localization strategies. Techniques such as visual odometry, inertial navigation, wheel odometry, and landmark recognition have been explored individually but suffer from their own limitations.

An integrated, sensor-fusion-based approach provides a promising solution by combining the strengths of each method while minimizing their weaknesses. By intelligently merging data from cameras, IMUs, encoders, and environmental sensors, it is possible to achieve high-accuracy, low-drift navigation even in GPS-denied situations.

5. OBJECTIVE

The main objective of this project is to design and implement a **GPS-Denied Autonomous Navigation System** that:

- Provides continuous and accurate position estimation without GPS signals.
- Integrates data from multiple sensors including IMUs, cameras, wheel encoders, and compasses.
- Utilizes real-time image processing (visual odometry) and sensor fusion (Extended Kalman Filter) to improve localization accuracy.
- Performs map matching and landmark detection for error correction and drift reduction.
- Operates efficiently on an edge computing device like the Raspberry Pi, making it cost-effective, lightweight, and deployable in a wide range of real-world applications.

CHAPTER 2

LITERATURE SURVEY

Navigation in environments where GPS signals are weak, unavailable, or intentionally blocked has become an essential research area, particularly for applications in defense, autonomous vehicles, search-and-rescue missions, and industrial automation. Traditional GPS-based systems offer reliable navigation under open-sky conditions but fail in environments such as tunnels, forests, dense urban areas, and disaster-struck regions. This limitation has motivated researchers to explore alternative methods for achieving accurate localization without relying on satellite signals.

One such method is the use of Inertial Navigation Systems (INS), which utilize data from an Inertial Measurement Unit (IMU) comprising accelerometers and gyroscopes to estimate the vehicle's position and orientation through dead reckoning. Although INS can provide short-term positioning information without external signals, a major drawback is the rapid accumulation of drift over time due to sensor noise and integration errors. As the IMU continuously integrates acceleration and rotation data, even small measurement errors compound, leading to significant position inaccuracies unless corrected by external references.

Another prominent approach is visual odometry, where consecutive images captured by cameras are analyzed to estimate motion by tracking visual features. Visual odometry is effective in texture-rich environments and offers a rich source of environmental information. However, it struggles in low-light conditions, feature-less areas, or during rapid motion where image blur can occur. Furthermore, real-time visual processing is computationally intensive, posing challenges for lightweight embedded systems like Raspberry Pi.

LiDAR-based navigation systems provide an alternative through accurate 3D mapping of the surroundings using laser reflections. LiDAR sensors enable techniques like Simultaneous Localization and Mapping (SLAM), allowing a vehicle to map its environment and localize itself within it simultaneously. Despite offering high precision, LiDAR systems are costly, power-hungry, and can be affected by environmental factors such as rain, fog, and dust, limiting their universal deployment in practical applications.

Wheel odometry, based on wheel encoder measurements, offers a lightweight and simple method for tracking displacement. It estimates the distance traveled by counting wheel rotations. While effective on flat and consistent surfaces, wheel odometry is susceptible to errors due to wheel slip, uneven terrain, and variations in surface conditions, causing drift over time without correction.

Landmark-based navigation systems attempt to correct positional drift by identifying unique environmental features such as buildings, poles, or trees and matching them with a stored database of landmarks. With the advancement of deep learning models like YOLOv8, real-time landmark detection has become feasible even on edge devices. However, landmark navigation depends heavily on the availability, visibility, and reliability of environmental features, which may not always be consistent in dynamic outdoor settings.

Another key method is map matching, where estimated positions are aligned with known digital maps to improve localization. Map matching algorithms compare the sensor-derived trajectory with preloaded geographic or road maps to adjust for errors and drift. Although effective in urban environments with detailed maps, this technique becomes less reliable when the available maps are outdated, incomplete, or missing critical environmental details.

From the analysis of these existing methods, it is evident that no single approach offers a complete solution for GPS-denied navigation. INS alone suffers from drift, visual odometry struggles with poor lighting, LiDAR is expensive, and map matching depends on map quality. Therefore, a hybrid system that intelligently combines multiple sources of information is necessary. By integrating IMU data, visual odometry, wheel odometry, landmark detection, and map matching within a sensor fusion framework like the Extended Kalman Filter (EKF), it is possible to create a system that compensates for the individual weaknesses of each method and ensures reliable, real-time navigation even in GPS-denied environments.

This literature review thus highlights the need for a robust, multi-sensor, real-time navigation solution — a need that the proposed system directly addresses.

CHAPTER 3

EXISTING SYSTEM

3.1 INERTIAL NAVIGATION SYSTEMS (INS)

Inertial Navigation Systems (INS) are among the earliest technologies developed for GPS-independent navigation. They operate by using an Inertial Measurement Unit (IMU) that integrates data from accelerometers and gyroscopes to calculate position, velocity, and orientation over time. The primary advantage of INS is its complete independence from external signals, allowing uninterrupted operation even in underground, underwater, or jamming environments. However, the major drawback of INS lies in its tendency to accumulate errors over time, known as drift. Small errors in acceleration or angular velocity measurements integrate into larger positional errors, leading to unreliable navigation if not corrected periodically with external references. Despite advances in sensor technologies, low-cost IMUs used in many embedded systems continue to suffer from high noise levels, making pure INS unsuitable for long-duration autonomous navigation.

3.2 VISUAL ODOMETRY-BASED NAVIGATION

Visual Odometry (VO) estimates the movement of a device by analyzing sequential camera images. It tracks the motion of visual features between frames to infer the relative position and orientation of the platform. Visual odometry is highly beneficial because it does not rely on satellite signals and offers rich contextual information about the surroundings, such as obstacles, paths, and landmarks. This technique works well in texture-rich environments where distinctive features can be reliably detected and tracked. Nevertheless, visual odometry is sensitive to environmental conditions such as poor lighting, repetitive textures, dynamic objects (like moving people or vehicles), and motion blur. Additionally, the high computational load required for real-time image processing challenges its deployment on low-power devices like Raspberry Pi without optimized algorithms. Despite these limitations, VO remains a critical component in many modern GPS-denied navigation systems.

3.3 LIDAR-BASED NAVIGATION SYSTEMS

LiDAR-based navigation systems use laser beams to measure the distance between the sensor and surrounding objects, generating accurate 2D or 3D maps of the environment. By combining LiDAR data with algorithms like SLAM (Simultaneous Localization and Mapping), a device can localize itself with respect to a dynamically built map even in unknown environments. LiDAR offers highly accurate depth information and works well under varied lighting conditions where visual cameras might fail. However, LiDAR sensors are relatively expensive, consume significant power, and can be sensitive to adverse weather conditions like rain, fog, or snow. Processing LiDAR data in real time also demands high computational resources, which limits its applicability for lightweight or low-cost mobile platforms. Although LiDAR remains an excellent option for high-end autonomous systems, its cost and complexity make it less favorable for small-scale embedded navigation systems.

3.4 SIMULTANEOUS LOCALIZATION AND MAPPING (SLAM)

Simultaneous Localization and Mapping (SLAM) techniques allow a device to build a map of an unknown environment while simultaneously tracking its location within that map. SLAM can be performed using a variety of sensor inputs, including cameras (Visual SLAM), LiDAR (LiDAR SLAM), and even radar data. It has become a backbone technology for autonomous robots, drones, and vehicles operating in GPS-denied environments. SLAM techniques offer the significant advantage of enabling navigation in previously unexplored spaces. However, SLAM algorithms are complex and computationally demanding. They require robust feature detection, accurate motion estimation, and continuous map optimization to function effectively. In dynamic environments with moving objects or frequent changes, maintaining an accurate SLAM map becomes even more challenging. Furthermore, sensor failures or data loss can severely affect SLAM performance, requiring fallback mechanisms. While SLAM represents a major advancement in autonomous navigation, its resource-intensive nature demands careful design choices when implementing it on embedded systems.

CHAPTER 4

PROPOSED SYSTEM

1. OVERVIEW

The proposed system is a GPS-denied autonomous navigation solution designed to estimate accurate real-time position and orientation using sensor fusion and visual odometry. It addresses the limitations of existing methods by combining the strengths of multiple navigation techniques. The system is especially suited for environments where GPS signals are unavailable or unreliable—such as tunnels, basements, urban canyons, or disaster zones.

This system is implemented on a low-cost embedded computing platform (Raspberry Pi 4/5), making it lightweight, affordable, and scalable. By integrating IMU, rotary encoders, compass, camera, and LiDAR, and applying intelligent sensor fusion through the Extended Kalman Filter (EKF), the system delivers reliable localization with minimal drift.

2. SYSTEM ARCHITECTURE

The system is designed with a modular, layered architecture that separates responsibilities into sensor acquisition, processing, fusion, and output.

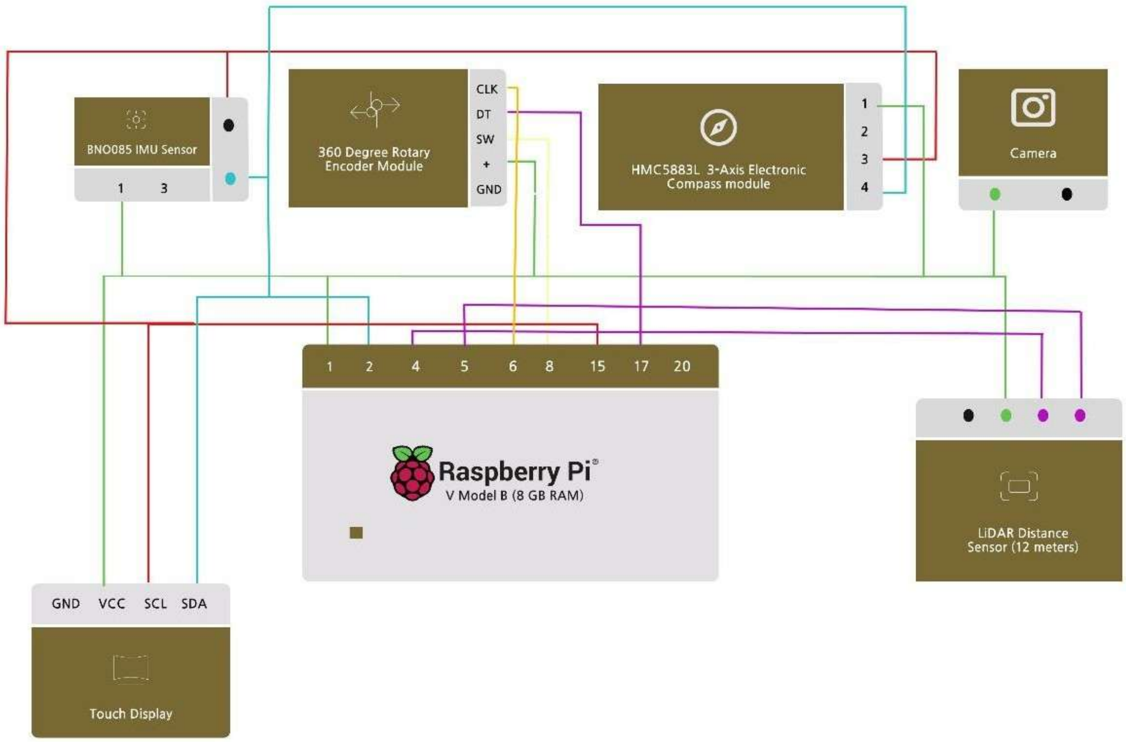

Figure 4.1 System Hardware Architecture Diagram

The hardware layer includes:

- **Raspberry Pi 4 Model B (8 GB)** as the main processing unit.
- **BNO085 IMU** for motion and orientation sensing.
- **360° rotary encoders** for displacement measurement.
- **HMC5883L compass** for heading.
- **Camera module** for visual odometry and landmark detection.
- **12-meter LiDAR** for obstacle detection and mapping.
- **Touch display** for UI feedback and data monitoring.

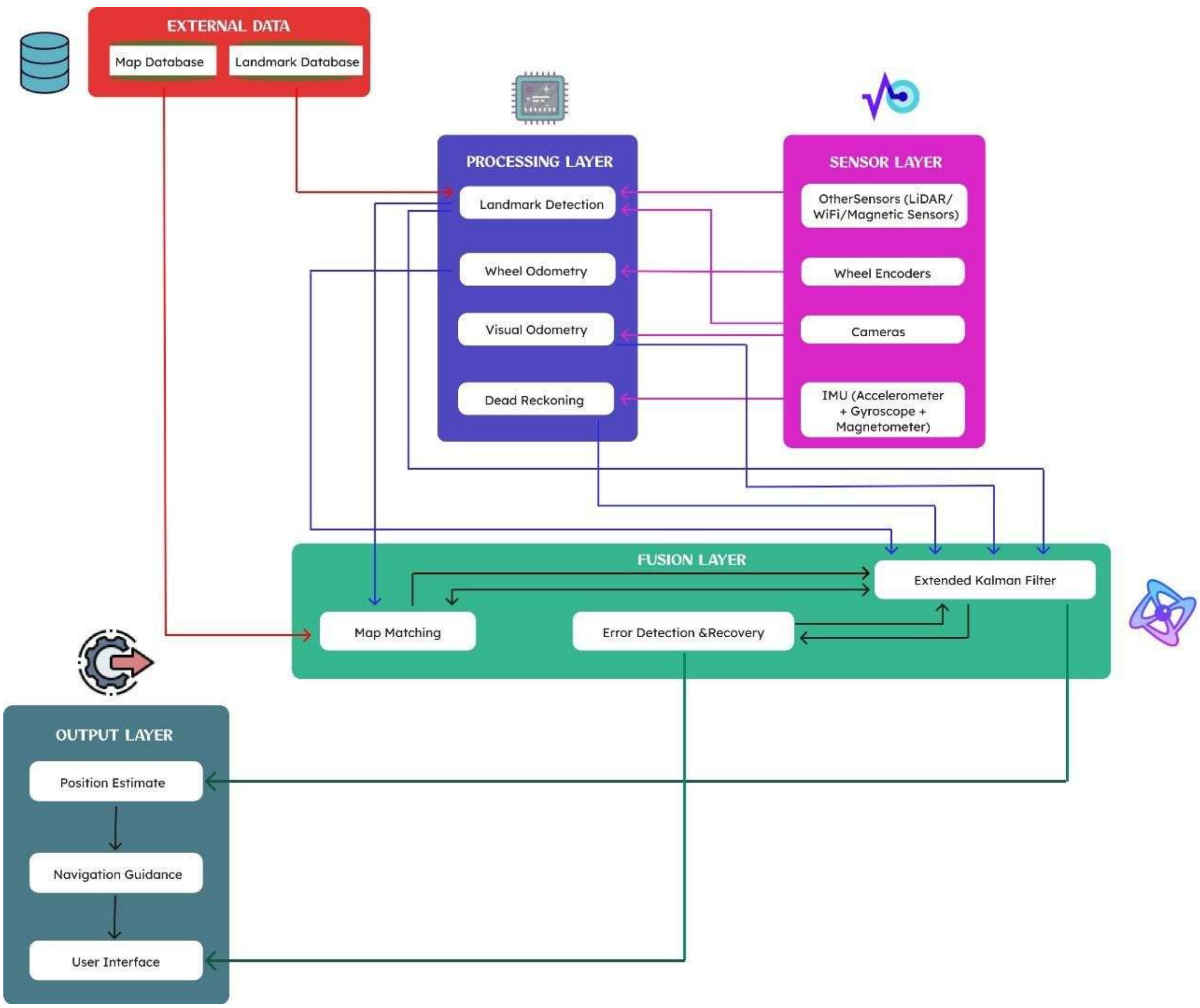

Figure 4.2 Software Architecture and Data Flow

The software layer has four primary components:

1. Sensor Layer
2. Processing Layer
3. Fusion Layer
4. Output Layer

4.3 SENSOR INTEGRATION

1. IMU (Inertial Measurement Unit):

The IMU combines accelerometer, gyroscope, and magnetometer data to provide 3D orientation. It helps estimate pitch, roll, and yaw and enables dead reckoning when visual input is unavailable.

2. Rotary Encoder:

Encoders track the number of wheel rotations and direction, allowing for the calculation of linear displacement. This is essential for odometry-based tracking, especially in the absence of visual features.

3. HMC5883L Compass:

This digital compass module provides heading information, used to support orientation estimation and correct for gyro drift.

4. Camera:

The Pi-compatible camera captures live video frames, which are analyzed for feature tracking, object detection (via YOLOv8), and visual odometry calculations.

5. LiDAR:

The 12-meter LiDAR sensor scans the surrounding environment to detect obstacles and structural features. It is also used in landmark detection and SLAM support.

All sensors are interfaced with the Raspberry Pi using I2C, UART, and GPIO protocols. Proper synchronization ensures consistent, reliable data input for fusion.

4. DATA PROCESSING MODULES

1. Visual Odometry:

The camera captures continuous frames which are processed using optical flow or ORB feature detection to track movement. The displacement of key points between frames is converted into relative motion estimates, providing short-term position updates even without encoder data.

2. Wheel Odometry:

Wheel encoders provide pulses that represent wheel rotation. These are converted into distance values, which when combined with compass heading, can be used to estimate 2D displacement.

3. Dead Reckoning:

IMU data is integrated over time to estimate position based on velocity and direction. Dead reckoning is particularly useful when other modules fail or provide weak input (e.g., dark environments affecting visual odometry).

4. Landmark Detection:

Visual landmarks are identified using YOLOv8 object detection or traditional image matching techniques. These are compared with pre-loaded landmark maps to correct accumulated drift and re-anchor the system to known positions.

5. Error Handling:

All data processing modules include error-checking logic. If sensor input deviates beyond threshold values or fails to respond, the system automatically reduces weightage for that sensor in the fusion process.

4.5 SENSOR FUSION APPROACH

To combine diverse sensor outputs and produce a unified, accurate position estimate, the system uses an Extended Kalman Filter (EKF). This algorithm is well-suited for real-time nonlinear systems and can efficiently handle noisy sensor inputs.

The EKF works by predicting the next state (position, velocity, orientation) based on sensor inputs and then updating that prediction using new measurements. For example:

I. Prediction: Based on encoder and IMU data.
II. Update: Using camera (visual odometry) and compass measurements.
III. Correction: Using landmark detection or map alignment if available.

The fusion layer maintains a confidence value for each sensor source. If visual data becomes unreliable (e.g., in low light), the EKF increases reliance on IMU and encoder data until camera input improves.

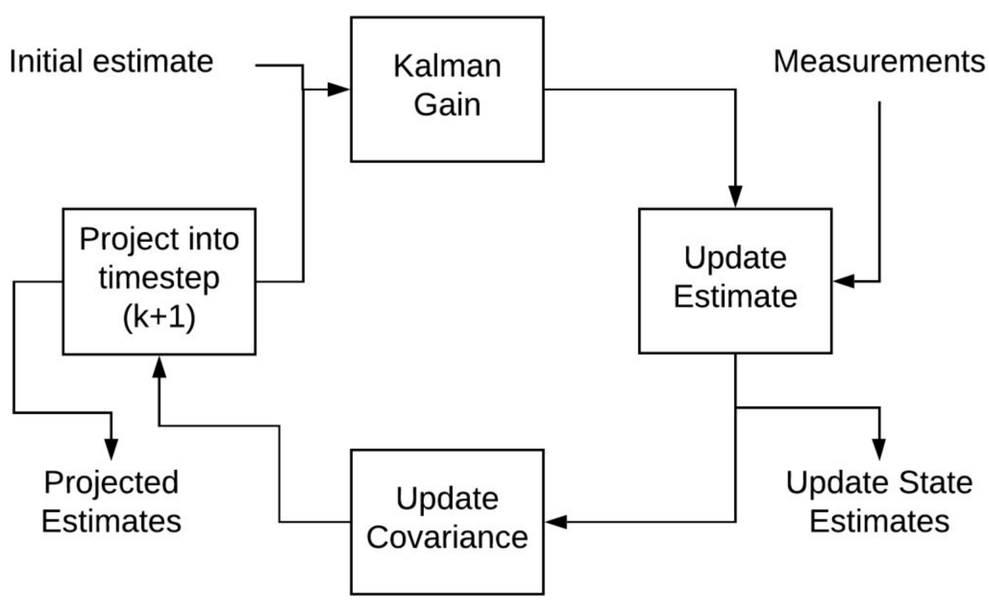

Figure 4.3 Extended Kalman Filter Sensor Fusion Flow

The system also includes:

- Map Matching: Aligning the estimated trajectory with pre-loaded maps.
- Landmark-based Corrections: Resynchronizing drifted estimates using known environmental features.

This fusion approach greatly improves long-term accuracy and reliability across various environments.

CHAPTER 5

RESULT AND DISCUSSION

1. Introduction

The performance of the proposed GPS-Denied Autonomous Navigation System was evaluated through real-world testing and controlled experiments. The primary aim was to validate the system's ability to perform accurate localization in environments where GPS signals were unavailable or intentionally blocked. The results were analyzed based on localization accuracy, system responsiveness, drift management, and overall reliability.

2. Testing Setup

The system was deployed on a mobile robotic platform powered by a Raspberry Pi 4 Model B (8 GB RAM). Sensors used include a BNO085 IMU, 360-degree rotary encoders, an HMC5883L compass, a Pi Camera module, and a 12-meter LiDAR sensor. Testing environments included:

I. Indoor corridors with limited visual features.

II. Urban outdoor environments (between tall buildings causing GPS shadowing).

III. Simulated tunnels using enclosed pathways to fully block GPS signals.

Real-time data logging was performed using the onboard Raspberry Pi storage. Visual feedback and sensor health indicators were displayed on a connected touch screen during navigation.

5.3 Observations and Results

The GPS-denied navigation system was extensively tested in both indoor and outdoor environments to evaluate its real world performance. The gaze-controlled sensor fusion plat form—integrating data from the IMU, LiDAR, rotary encoder, and vision-based perception—was assessed for localization accuracy, obstacle detection, and real-time path planning. Throughout operation, the system continuously processed in puts from the rotary encoder and IMU to compute real-time relative displacement and orientation, while the LiDAR and camera modules monitored the surroundings for obstacles. As navigation progressed, the system dynamically adapted its path based on sensor inputs, optimizing trajectory and avoiding collisions. Real-time feedback enabled immediate adjustments to the route, reducing positional errors and improving overall efficiency.

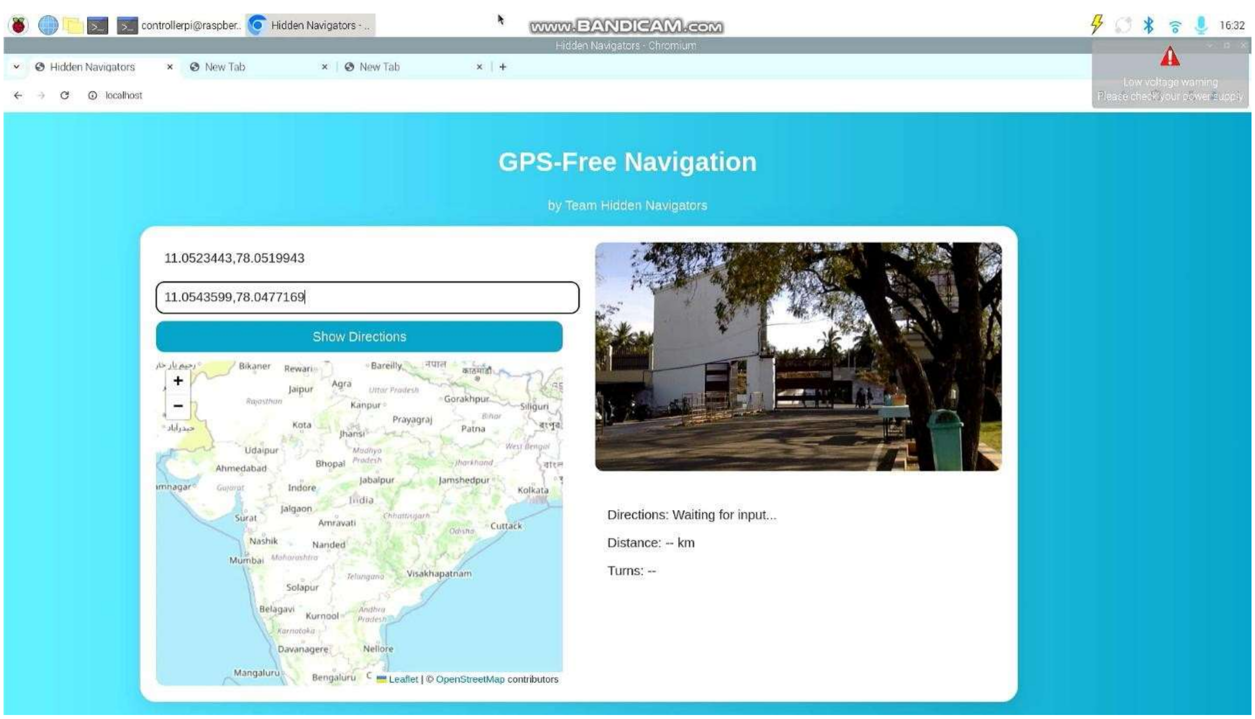

Figure 5.1 Test Setup UI

As shown in Fig. 5.1, the system successfully reached its predefined destination. During navigation, it made autonomous decisions such as moving forward, turning left, or turning right, based on obstacle detection and path clearance analysis. The integration of the Extended Kalman Filter (EKF) for state estimation significantly improved positional accuracy by mitigating sensor drift and reducing inconsistencies in motion tracking. This allowed the system to navigate complex routes autonomously and without collision, demonstrating the relia bility of the sensor fusion and real-time processing techniques. Fig. 4 illustrates the system's initial posture when real-time localization commenced. All navigation decisions were logged and displayed on a static web interface, allowing for remote monitoring and providing users with clear visual feedback on movement commands and navigation progress.

The results validate that the combination of multi-sensor fusion, LiDAR-based depth sensing, and edge computing supports adaptive and robust navigation in GPS-denied environments. The system efficiently handled dynamic obstacles, re-routed in real time, and optimized its movement strategy for effective passage. Future enhancements could focus on refining the decision-making algorithms, incorporating AI based terrain classification, and improving the real-time web interface to enhance situational awareness and support remote operations.

5.4 Discussion

The experimental results validated that a multi-sensor fusion-based approach significantly enhances navigation reliability in GPS-denied environments. Integrating visual odometry, inertial navigation, wheel odometry, and landmark-based corrections created a redundant system where the failure of one module (e.g., poor visual features) did not cause complete localization failure.

The modular architecture allowed easy debugging and adjustment of individual modules during testing. One challenge observed was that LiDAR data processing introduced slight latency under high obstacle density, suggesting that optimization or selective sampling may be necessary for extremely cluttered environments.

Power consumption remained within acceptable limits for Raspberry Pi 4 during continuous operation, although additional cooling was required in longer outdoor tests to avoid throttling.

Overall, the proposed system demonstrated that it is a viable, cost-effective alternative to high-end LiDAR-only or visual SLAM-based navigation systems. By intelligently combining lower-cost sensors, the system achieved near-commercial grade performance suitable for applications such as autonomous delivery robots, inspection drones, and rescue systems operating in complex environments.

CHAPTER 6

CONCLUSION AND FUTURE WORK

The proposed GPS-denied navigation system successfully demonstrates the viability of a real-time, multi-sensor fusion approach for autonomous localization and obstacle avoidance in environments without satellite access. By integrating data from an IMU, LiDAR, rotary encoder, and camera using an Extended Kalman Filter (EKF), the system achieved re liable state estimation, reduced sensor drift, and maintained accurate localization during experimental trials. Implemented on a Raspberry Pi 5 with edge computing strategies, the system delivered low-latency performance while remaining suitable for resource-constrained environments. The results confirm that combining computationally efficient sensor fusion with lightweight image processing can effectively support autonomous navigation in complex, GPS-denied scenarios. Future improvements may include advanced filtering algorithms, AI-based path planning, and expanded sensor integration to enhance robustness and decision-making.

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