ABSTRACT

In this work, we propose a robust framework,to navigate in GPS-denied environments. While the Global Positioning System (GPS) is widely used for navigation, mapping, and tracking, it becomes unreliable in specific scenarios such as tunnels, areas surrounded by skyscrapers, or during satellite connectivity issues.

From the existing literature, we observe that the Inertial Measurement Unit (IMU) offers an alternative positioning system. However, IMU-based navigation introduces significant drift over time, with a standard drift of approximately 1.04 meters as reported in research.

To overcome this limitation, we propose a system that leverages multimodal data sources, including **vision cameras, and IMU**, to provide accurate and reliable navigation support in GPS-denied environments.

Contents

List of Figures

.

List of Tables

Chapter 1 Introduction

The modern autonomous systems often rely on GPS for navigation because it's simple to use and reasonably accurate. GPS helps pinpoint an object's location within a certain margin of error. However, depending too much on GPS can become a problem, especially in situations where GPS signals are unavailable, such as during conflicts or in areas with poor signal reception, like inside buildings or in crowded cityscapes.

To address these limitations, researchers are focusing on alternative navigation methods, such as inertial navigation systems (INS). These systems use internal sensors, like accelerometers, to estimate position based on the system's movement. While this approach shows promise, it also has challenges, mainly due to sensor errors.This study explores and works on optimizing these alternative navigation methods and tries to overcome the limitations in the previous research .

1.1 Motivation

Autonomous systems play a crucial role in military ,rescue operations, especially in situations where human lives are at high risk. These systems take over tasks usually performed by people, reducing the burden on personnel. With growing demand from the military for unmanned and autonomous systems, these systems are now expected to function in a wider range of environments. However, traditional GPS solutions often fail in certain conditions.

To make autonomous systems more versatile and reliable, we need alternative ways to calculate their position in environments where GPS doesn't work or is no longer practical.

1.2 Objectives

- To design a navigation system for GPS-denied environments that integrates visual odometry (VO) and inertial odometry (IO) for accurate localization.
- To enhance accuracy and reduce noise by fusing sensor data using a Kalman filter.
- To ensure adaptability and precision for autonomous systems in challenging terrains, supporting critical applications like disaster relief and autonomous driving.

1.3 Literature survey

In the [1], it proposes a robust and highly efficient feature-based visual-inertial odometry (VIO) approach. In order to save the computational resource, a simplified stereo visual model is applied to reduce the dimension of visual measurements. Moreover, the speed of feature matching is improved by using prior information from the inertial sensor. And through the marginalization, optimization is limited in two sliding windows, which can meet the need for the real-time application.

In the [2], Design of Sensor Fusion Driver Assistance System for Active Pedestrian Safety, proposes a sensor fusion system for pedestrian detection that combines a camera and a 1D Light Detection and Ranging (LiDAR) sensor. The system uses two object detection methods: one based on optical flow from the camera and the other using distance measurements from the LiDAR. The two sensors complement each other, with the LiDAR providing accurate longitudinal distance measurements and the camera providing lateral movement information. The authors tested their system in real-world environments and found it to be highly accurate and robust in various conditions, including night time, shadows, and the presence of multiple pedestrians. They suggest that future work could improve the system's performance by using Bayes' theorem to reduce false positives from the optical flow algorithm

In [3], it introduces a novel hybrid approach that leverages the inherent strengths of traditional VIO techniques, while harnessing the potential of advanced machine learning technologies. By seamlessly integrating an iterated extended Kalman filter with deep learning techniques, our approach systematically takes into account uncertainties, thereby enhancing the overall reliability and robustness of the system. The proposed algorithm has been rigorously evaluated on the KITTI and EuroC datasets, outperforming other deep learning VIO methods.

1.4 Problem statement

To develop a multimodal sensor fusion technique that fuses data from sensors which aids in seamless navigation in GPS-denied environments.

1.5 Application in Societal Context

- **Disaster Response and Search Operations**: During natural disasters like earthquakes or floods, GPS signals can be unreliable. Systems capable of navigating without GPS can assist in locating survivors, delivering aid, and mapping inaccessible areas.
- **Healthcare Delivery in Remote Areas**: Autonomous vehicles equipped with GPS-independent navigation can deliver medical supplies and vaccines to remote or densely forested regions where GPS signals may be weak.

1.6 Project Planning and Bill of materials

Project Planning:

The use of pure visual odometry technique to calculate position is found to cause a large scaling error. The inertial measurement unit causes a large drifting error by accumulating smaller errors when double integrating the acceleration to find the position.

Our framework collects data from the Camera and the Inertial Measurement Unit (IMU) sensor. The data obtained is then fused with the help of Kalman filter to obtain an estimate of the position of the moving setup.

Bill of Materials:

Component	Specifications	Quantity	Estimated Cost (INR)
MPU6050 (IMU)	Triple-axis accelerometer and gyroscope, I2C protocol	1	₹200
RGB Camera	1080p resolution, 30-60 FPS, wide-angle lens	1	₹2,500
Processing Unit	Raspberry Pi or Arduino	1	₹800
Power Supply	Rechargeable Battery Pack, Capacity: 6000mAh	1	₹200
Connectors and Wires	For sensor interfacing	-	₹100
	Total Estimated Cost		₹3,800

Table 1.1: Bill of Materials

Chapter 2 System design

2.1 Functional block diagram

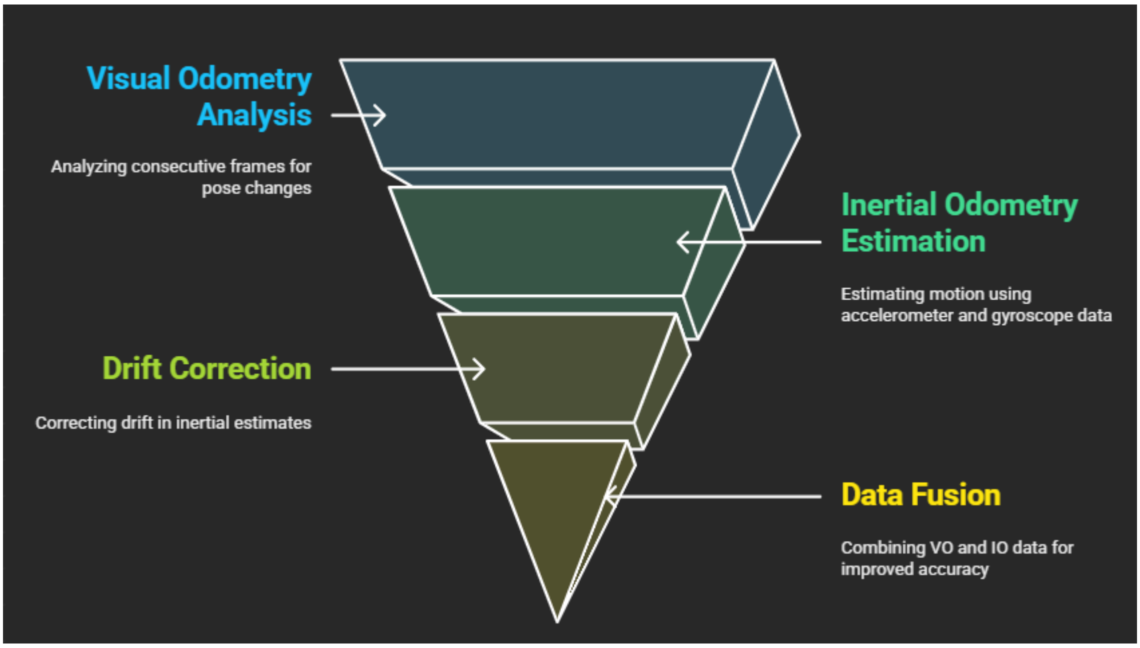

Figure 2.1: Functional Block Diagram

2.2 Design alternatives

Multi-Sensor Fusion with LiDAR

- Incorporate LiDAR for precise depth sensing and fuse it with IMU and visual odometry data using Extended Kalman Filters (EKF) or Graph-based optimization.

Wheel Odometry Fusion

- Add wheel encoders to the system to measure displacement and orientation changes. Fuse this data with VO and IO using a Kalman filter

2.3 Final design:

Our final design consisted of a RGB camera and an IMU(MPU-6050).The data obtained from the **visual odometry** and the **inertial odometry** was then fused using **Kalman Filter**.

Visual Odometry (VO): Utilizes ORB (Oriented FAST and Rotated BRIEF) for efficient feature extraction and matching, ensuring rotation and scale invariance. Consecutive frame analysis provides relative pose changes like translation and rotation.

Inertial Odometry (IO): Relies on IMU data (accelerometer and gyroscope) to estimate short-term motion. While accurate in the short term, it suffers from drift over time due to sensor noise and biases.

Data Fusion with Kalman Filter: Combines VO and IO to leverage their strengths. IO provides continuous updates, while VO corrects drift, ensuring robust position and orientation estimates.

Chapter 3 Implementation details

3.1 Specifications and final system architecture

Visual Odometry:

- **ORB** (Oriented FAST and Rotated BRIEF) is a computationally efficient feature detection and description algorithm for tasks like VO.
- ORB uses the FAST (Features from Accelerated Segment Test) algorithm to detect keypoints (e.g., corners or edges) in an image.
- ORB matches keypoints between consecutive frames by comparing their binary descriptors using Hamming distance.
- Matched keypoints are used to compute the Fundamental Matrix.
- Once the Essential Matrix is computed, it is decomposed to extract the relative rotation (R) and translation (t) between frames.

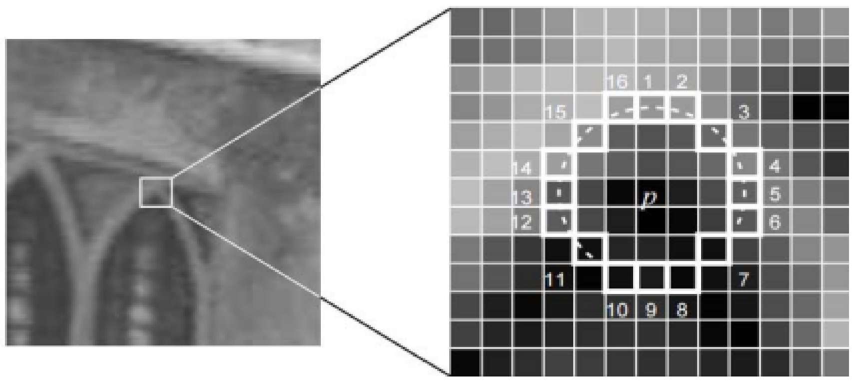

Fig .3.1 Images are preprocessed (e.g., grayscale conversion, distortion correction).

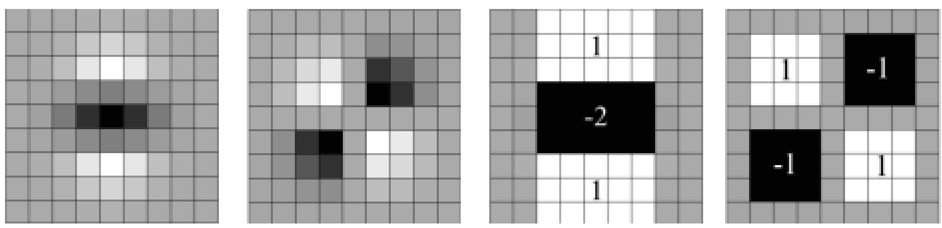

Fig .3.2 ORB identifies keypoints and computes binary descriptors for each frame.

Inertial odometry:

Dead Reckoning uses accelerometer and gyroscope data to estimate position by integrating velocity and orientation over time.

Timestamp synchronization: Data timestamps and compared with each other, If the difference is within a predefined threshold (Q), you select the IMU and VO data pairs as synchronized. This ensures that the data used for processing, such as Kalman filtering, corresponds to the same moment in time, improving the accuracy of sensor fusion, ie **|VO - IO| < Q.**

Kalman Filter:

The primary goal is to estimate the system's state (position, velocity, and orientation) accurately by fusing data from your IMU (Inertial Odometry) and Visual Odometry (VO) components.

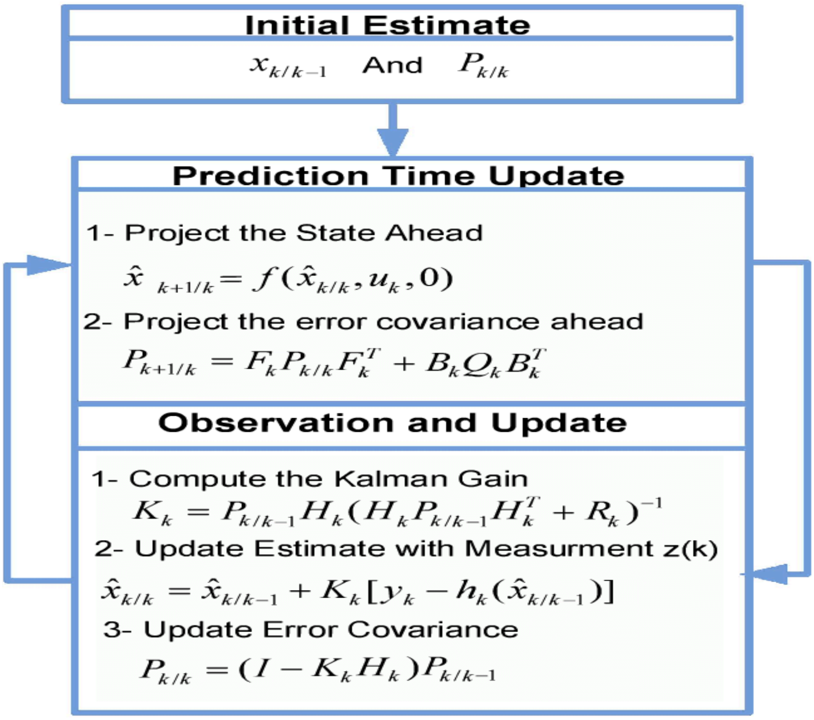

Fig.3.3 Kalman Filter design

State Representation:The state vector is defined as: State:[x,y,z,vx,vy,vz]T ,It includes position (x,y,z) and velocity (vx,vy,vz)
Steps in Kalman Filter:
Prediction Step:
Using the state transition model, the current state is predicted from the previous state using IMU-based accelerations.
Update Step:
When a VO measurement (position) is available, it is fused with the predicted state
Inputs to the Kalman Filter:
Prediction Input: Accelerometer data from IO as control input (u).
Measurement Input: Position data from VO as measurements (z).

3.2 Algorithm

Step1: Sensor Data Acquisition

IMU Sensor (MPU6050) provides acceleration and angular velocity data using its built-in accelerometer and gyroscope.

RGB Camera captures image frames at a resolution of 1080p and a frame rate of 30-60 frames per second, providing visual data for feature tracking and pose estimation.

Step2: Timestamp Synchronization

Synchronizes the data streams from the IMU and camera to ensure that the measurements align in time. This is crucial for accurate fusion, as both sensors operate at different frequencies and must correspond to the same instant.

Step3: Synchronized Data Fusion

The synchronized IMU and visual data are passed to a Kalman Filter, a mathematical algorithm that combines these inputs. The IMU provides continuous motion estimates, while the camera corrects drift by analyzing visual information.

Step4: Output

The Kalman Filter processes the fused data to compute position, velocity, and orientation with enhanced accuracy, which are then used for navigation purposes.

3.3 Flowchart

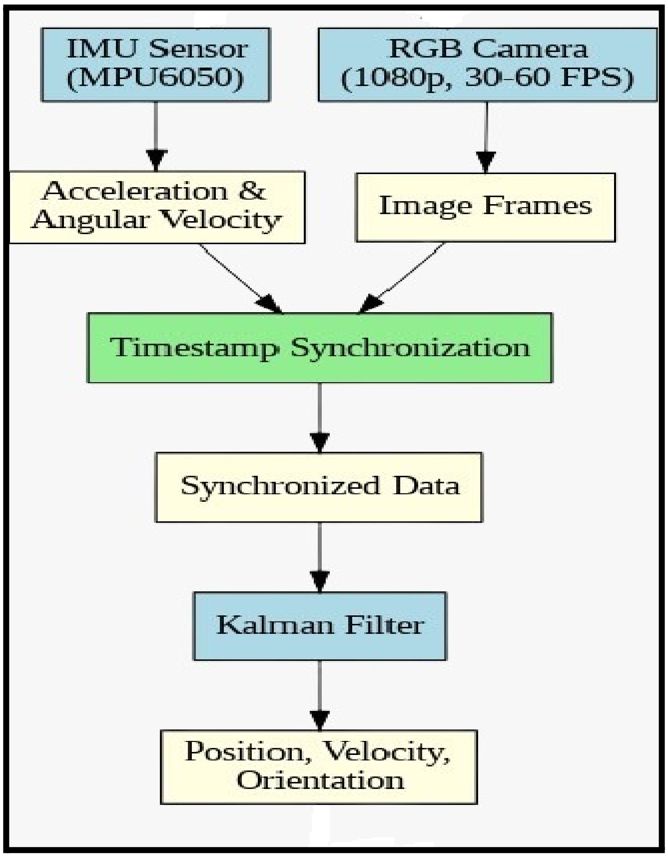

Figure 3.4: Functional Block Diagram

Chapter 4 Optimization

4.1 Introduction to optimization

The Kalman Filter is a method used for estimating the state (e.g., position, velocity) of a system while accounting for uncertainty due to noise in motion and sensor data. It represents the state as a Gaussian distribution, defined by its mean (most likely value) and covariance (uncertainty).

For systems with linear models, the Kalman Filter works efficiently, but real-world systems are often nonlinear. To address this, the Extended Kalman Filter (EKF) approximates the nonlinear models using linearization techniques

1. **Linearization**: Nonlinear functions (motion and sensor models) are approximated as linear functions near the current estimate using the first-order Taylor expansion. This involves calculating the Jacobian matrix, which represents the slope of the nonlinear function.
2. **Prediction and Update**:
    - Predict the next state using the motion model.
    - Update the prediction using sensor data, adjusting for noise.
3. **Gaussian Assumption**: EKF maintains the state estimate as a Gaussian distribution, even after applying nonlinear models.

The EKF trades exactness for efficiency, making it a practical choice for many real-world, nonlinear systems like robotics and navigation.

4.2 Types of Optimization

Use of Extended Kalman Filter:

The EKF extends the KF to handle nonlinear systems by linearizing the motion and observation models.

Key Challenges with Nonlinear Systems

1. Nonlinear functions (g,hg, hg,h) cannot directly produce Gaussian outputs.
2. Passing a Gaussian through a nonlinear function often results in a non-Gaussian distribution, requiring approximation.

Solutions in EKF

Taylor Series Expansion: Approximate the nonlinear functions and h observation model using a first-order Taylor expansion around the current estimate.

Jacobian Matrices: Derivatives of g and h are computed with respect to the state. These Jacobian matrices replace the linear transition and observation matrices used in the standard KF.

4.3 Selection and Justification of the Optimization Method: Extended Kalman Filter (EKF)

The Extended Kalman Filter (EKF) is a robust method for solving optimization problems in nonlinear dynamic systems. Here's why it is an appropriate choice and its justification for use:

Selection of EKF:

The EKF is chosen as the optimization method when:

1. The System is Nonlinear:
    - EKF handles nonlinear systems by linearizing them around the current estimate using a first-order Taylor expansion.
2. Gaussian Noise Assumptions Hold:
    - EKF assumes that the process noise and measurement noise are Gaussian-distributed, which is common in real-world systems.
3. Real-Time State Estimation is Required:
    - EKF is efficient enough for real-time applications, making it ideal for dynamic systems such as tracking, localization, or navigation.
4. Iterative Updates are Needed:
    - EKF operates in a recursive manner, constantly refining the state estimate based on new measurements.

Justification of EKF:

1. Handling Nonlinearities

- In navigation, the system's motion may involve nonlinear dynamics (e.g., turning), which EKF can model effectively.

2. Efficient Use of Resources

- Nonlinear optimization techniques like particle filters can be computationally intensive, particularly for high-dimensional systems. EKF uses Jacobian matrices to linearize the system, avoiding the need for extensive computation while maintaining accuracy

Justification of EKF:

1. Handling Nonlinearities

- In navigation, the system’s motion may involve nonlinear dynamics (e.g., turning), which EKF can model effectively.

2. Efficient Use of Resources

- Nonlinear optimization techniques like particle filters can be computationally intensive, particularly for high-dimensional systems. EKF uses Jacobian matrices to linearize the system, avoiding the need for extensive computation while maintaining accuracy.

Chapter 5 Results and discussions

5.1 Result Analysis

- **VO data collected format:**
  {'timestamp': 1735648467.2991047, 'position': [-0.9656401, -0.05987403, -0.00214024893], 'orientation': [-4.959923524, -1.41657827, 0.000844460]}
- **IO data collected format:**
  {'timestamp': 1735648467.2891047, 'acceleration': [-0.04, -0.05,-0.94], 'orientation': [-4.87, -0.34, 0.08]

- Sampling rate of Camera and IMU is set to **20Hz** to avoid timestamp synchronization problem and setting the threshold to 0.05.

- Collected data for testing: Using an RGB camera and an IMU, we traveled along a straight path for 10 meters, then made a left turn and continued for another 10 meters.

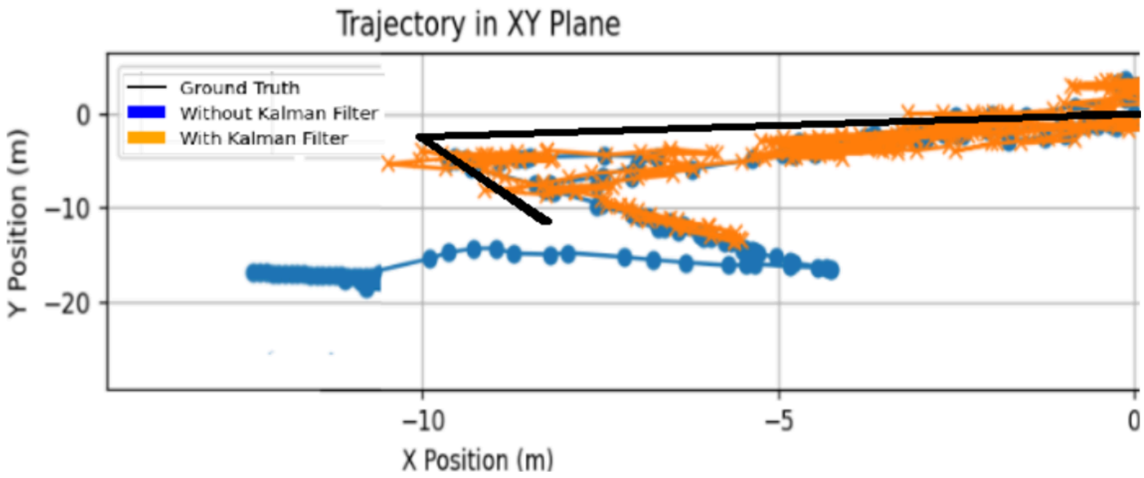

figure 5.1 transversal path in xy plane

5.2 Discussion on optimization

Ground Truth	Without optimization	Optimization
First 5 m	7 m	5 m
Next 5 m	6 m	6 m
Left deviation 5 m	9 m	7 m
Next 5 m	7 m	5 m

Table 5.1 comparative analysis of distance travelled

- The optimization was done using Extended Kalman Filter and the results are documented in the table.

- The odometry data for 20 metres was obtained using camera and IMU. The overall distance measurement without optimization added up to 29 metres and after optimizing it was found to be 23 metres.

- Therefore the Extended Kalman Filter is efficient and accurate in handling nonlinearities caused due to deviation in the path.

Chapter 6

Conclusions and future scope

6.1 Conclusion

In this project, we have successfully developed a technique tailored for GPS-denied environments, addressing the challenges posed by limited satellite connectivity. By leveraging sensor integration, such as Camera and IMU, and employing robust algorithms like the Extended Kalman Filter (EKF), we ensured accurate and reliable positioning. The system effectively estimates the travel path by processing fused data, demonstrating its capability to navigate dynamic and complex environments.

This approach not only provides a viable alternative to GPS but also lays the groundwork for further advancements in autonomous navigation systems.Future improvements could involve refining sensor fusion techniques, incorporating machine learning for enhanced decision-making, and extending the system's capabilities to larger, more diverse environments.

By addressing a critical limitation in conventional navigation, this project contributes significantly to the field of location-based technologies and opens up new possibilities for innovation in challenging environments.

6.2 Future scope:

- **Integration of Multi-Sensor Data**: Combine data from camera, IMU, LiDAR, and wheel encoders to enhance the system's accuracy and reliability, enabling robust navigation in complex environments.
- **Autonomous Vehicle Deploymen**t: Extend the system to fully autonomous vehicles, capable of real-time navigation and obstacle avoidance in both structured (urban) and unstructured (off-road) environments.
- **Scalability for Diverse Applications**: Adapt the system for various autonomous platforms, including delivery bots, industrial robots, and agricultural vehicles, broadening its practical use cases.

Bibliography

[1]Yang, G., Zhao, L., Mao, J., & Liu, X. (2019). Optimization-Based, simplified Stereo Visual-Inertial odometry with High-Accuracy initialization. IEEE Access, 7, 39054–39068.

[2]H. H. Tadjine, R. Roellig, K. Schulze and H. Daniel, "New methods and tools for the development and verification of safety functions during development of pedestrian detection systems," 2012 8th International Conference on Computing Technology and Information Management (NCM and ICNIT), Seoul, Korea (South), 2012, pp. 434-438.

[3]K. Duy Nguyen et al., "Learning Visual-Inertial Odometry With Robocentric Iterated Extended Kalman Filter," in IEEE Access, vol. 12, pp. 109943-109956, 2024, doi: 10.1109/ACCESS.2024.3440182.
keywords: {Deep learning;Feature extraction;Odometry;Visualization;Sensors;Kalman filters;Accuracy;Monocular camera;visual inertial odometry;iterated extended Kalman filter;deep learning},