Autonomous UAV navigation in post-disaster environments using ORB-SLAM

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Abstract

This paper investigates the feasibility of developing an autonomous navigation system for Unmanned Aerial Vehicles (UAVs) operating in GPS-denied and structurally compromised environments, using the ORB-SLAM algorithm as the core method. ORB-SLAM (Oriented FAST and Rotated BRIEF – Simultaneous Localization and Mapping) is a modern visual SLAM approach based solely on image data from mono or stereo cameras, without reliance on external positioning systems.

The main objective of the research is to evaluate the potential of ORB-SLAM as the foundation for an onboard UAV navigation module capable of operating independently in complex, unstructured environments. This is particularly relevant for post-disaster scenarios, including search and rescue missions, tactical reconnaissance, and rapid response in damaged infrastructures.

The study combines analytical modeling with experimental testing of an adapted ORB-SLAM configuration, addressing challenges of real-world input such as poor lighting, partial destruction of reference points, and dynamic scene elements. Results demonstrate that ORB-SLAM achieves high localization accuracy, robust trajectory recovery after tracking loss, and real-time map generation - all without dependency on GPS, IMUs, or external sensors, which is critical for lightweight aerial platforms.

Several limitations remain, including sensitivity to degraded visuals, reliance on distinctive scene features, and computational demands on edge devices. Nevertheless, the research confirms ORB-SLAM's suitability for compact, energy-efficient UAV navigation systems in GPS-denied environments. Future directions include sensor fusion, dynamic reconfiguration, and deployment in multi-agent systems. These findings highlight the practical value of ORB-SLAM-based navigation for disaster response and civil protection, offering a step toward safer and more resilient autonomous aerial operations.

Keywords

autonomous UAV navigation, GPS-denied environments, Visual SLAM, Computer vision, Real-time mapping

1. Introduction

Nowadays, we increasingly face emergencies such as natural disasters, industrial accidents, and armed conflicts. These events often cause severe damage to critical infrastructure. In such environments, rapid and accurate reconnaissance, detection of surviving objects, planning of rescue operations, and up-to-date mapping of affected areas are of paramount importance for effective decision-making.

Unmanned Aerial Vehicles (UAVs) represent one of the most efficient tools for addressing these tasks, as they enable remote observation while minimizing risks to the lives of military personnel, rescuers, and civil protection specialists. However, traditional navigation systems that rely on Global Positioning System (GPS) signals are not always available or reliable in complex operational scenarios – for example, in destroyed urban areas, underground facilities, inside buildings, or under conditions of active electronic countermeasures [1].

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This limitation highlights the need for autonomous navigation systems capable of ensuring UAV orientation without dependence on external positioning signals. A promising direction in this field is the use of visual Simultaneous Localization and Mapping (SLAM) algorithms. In particular, the ORB-SLAM technology enables spatial localization and environment mapping based solely on video streams from onboard monocular or stereo cameras, without requiring GPS support.

2. Research objective

The objective of this study is to investigate the feasibility of developing an autonomous navigation system for Unmanned Aerial Vehicles (UAVs) based on the ORB-SLAM algorithm, which enables spatial orientation exclusively through camera images, without reliance on satellite navigation systems (GPS).

The research involves analyzing the functional capabilities, advantages, and limitations of ORB-SLAM in structurally compromised or disaster-affected environments, as well as evaluating the potential effectiveness of this approach in practical applications, including search and rescue operations, tactical reconnaissance, and emergency response.

3. Related works

The problem of autonomous UAV navigation under conditions of limited GPS availability has attracted significant attention from the scientific community. Among the most well-known approaches are MonoSLAM, LSD-SLAM, DSO, and ORB-SLAM. Each of these methods has its advantages and limitations; however, ORB-SLAM stands out for its balance between accuracy, processing speed, and computational efficiency.

SLAM (Simultaneous Localization and Mapping) is a key approach in the field of autonomous navigation, enabling mobile devices such as drones or ground robots to simultaneously build a map of the environment and determine their position relative to it. Unlike systems that rely on pre-existing maps or GPS, SLAM allows a device to orient itself in unknown or dynamic environments – which is particularly important in disaster zones, indoor spaces, underground facilities, or under conditions of active signal jamming [2].

Among various SLAM algorithms, ORB-SLAM (Oriented FAST and Rotated BRIEF SLAM) occupies a special place as one of the most effective visual methods that relies solely on a camera for navigation [3]. It is built on a combination of two key computer vision techniques:

- FAST (Features from Accelerated Segment Test) – for fast detection of corner points in images;
- BRIEF (Binary Robust Independent Elementary Features) – for generating compact descriptors of these points, enabling efficient feature matching between frames [3].

The main advantages of ORB-SLAM include: the use of ORB descriptors, which ensure computational efficiency and stable real-time performance; high mapping and localization accuracy, making it suitable even for complex tasks in narrow or obstructed spaces; relatively low computational requirements, allowing implementation on compact single-board computers (e.g., NVIDIA Jetson, Raspberry Pi with cameras); and support for multiple operation modes: monocular, stereo, and RGB-D [4]. ORB-SLAM2 further extends the baseline model by adding support for stereo and RGB-D cameras, which is particularly relevant for applications requiring higher accuracy.

Visual SLAM methods are actively studied in the context of drones operating in complex environments. For example, [5] discusses the use of ORB-SLAM for navigation in collapsed buildings, while [6] describes its application in simulated rescue scenarios. Study [7] compares the performance of visual SLAM with inertial navigation under conditions of low illumination and dynamic scenes.

To assess the relevance of the topic, several practical implementations of similar systems were analyzed:

- Exyn Technologies (USA) – developed software for autonomous drone navigation in underground and GPS-denied environments. The system generates a 3D map of the environment in real time, adapting to new obstacles during flight. It has been applied in rescue operations, infrastructure inspection, and related domains [3].
- A research project based on ORB-SLAM3 – proposed a navigation system for low-cost drones equipped with a single RGB camera. This system enables UAVs to navigate in indoor environments with obstacles, detecting possible exits and restricted access zones [4].

In addition, hybrid approaches are being actively explored, where ORB-SLAM is complemented by data from IMUs, LiDAR, or ultrasonic sensors [8, 9]. Such integration improves system robustness against the loss of visual features, which is typical in destroyed infrastructures.

Another important research direction concerns edge computing and optimization of SLAM for embedded systems [10]. These solutions are highly relevant for the practical deployment of autonomous navigation on compact UAV platforms.

Thus, the scientific basis surrounding ORB-SLAM is broad and dynamically evolving. Nevertheless, there remains a strong need for specialized adaptations tailored to emergency reconnaissance in disaster-stricken environments, which underlines the relevance of this study.

4. Architecture of the autonomous UAV navigation system

Effective autonomous UAV navigation in conditions of complete or partial GPS unavailability requires the coordinated operation of both hardware and software components. The proposed system is based on the ORB-SLAM algorithm as the core of localization, combined with real-time modules for trajectory control.

The architecture of the autonomous navigation system includes the following main components:

- Camera – provides a continuous image stream for analysis. A monocular camera may be used to reduce computational load, while stereo or RGB-D cameras can enhance depth estimation accuracy;
- Computational unit – a single-board computer such as Raspberry Pi 4, Jetson Nano, or NVIDIA Xavier NX; supports hardware acceleration for real-time image processing; operates under Linux (Ubuntu with ROS-based middleware);
- Software – localization module (implementation of ORB-SLAM2 or ORB-SLAM3); mapping subsystem (Keyframes, Bundle Adjustment); synchronization module with the onboard Flight Control Unit (FCU).

The autonomous navigation algorithm operates according to the following sequence:

1. Image acquisition from the onboard camera (20–30 frames per second);
2. Pre-processing: detection of ORB keypoints and descriptors;
3. Localization: determining UAV position relative to previous frames;
4. Mapping: updating the three-dimensional representation of the environment;
5. Trajectory planning based on the generated map and mission objectives;
6. Transmission of coordinates to the trajectory controller;
7. Continuous update of the cycle in real time at up to 30 Hz.

The overall architecture of the ORB-SLAM system is presented in Figure 1, which illustrates the main modules and their interactions during mapping and camera pose tracking.

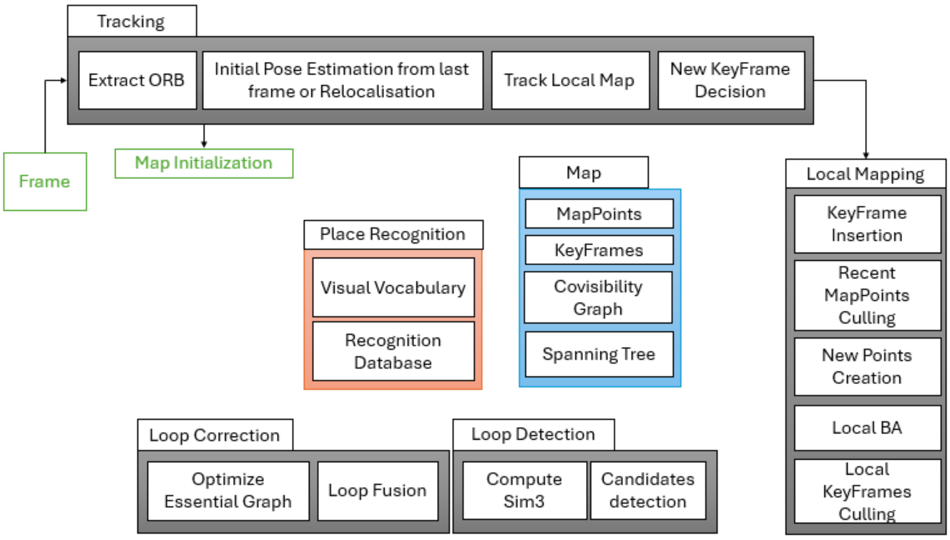

Figure 1: General architecture of the ORB-SLAM system.

To ensure precise path following, the navigation system transmits position and orientation data to the flight controller (PX4, Ardupilot, etc.) via MAVLink or ROS. The trajectory controller converts these coordinates into actuator commands for motors and stabilizers. In the event of tracking loss or failure to detect keypoints, the system switches to a trajectory recovery mode or initiates an emergency descent.

5. Experiments

The test scenario and model data for UAV ORB-SLAM navigation were developed in a simulation environment, representing drone movement within partially destroyed buildings under GPS-denied conditions (Tabl.1). The UAV was equipped with a monocular camera, and the ORB-SLAM algorithm processed the image stream in real time.

Table 1
Example of Simulated Input Data and ORB-SLAM Behavior

№	Input Frame	Lighting / Conditions	No. of ORB points	Matches	Estimated Position (X, Y, Z) [m]	Expected Behavior
1	frame_001	normal	220	-	(0.0, 0.0, 0.0)	Initialization
2	frame_002	normal	208	198	(0.15, 0.03, -0.01)	Accurate localization, map update
3	frame_003	dimmed	180	160	(0.30, 0.06, -0.01)	Slight degradation, but stable operation
4	frame_004	shadows	100	85	(0.45, 0.08, -0.02)	Tracking unstable, but maintained
5	frame_005	heavily dimmed	40	15	-	Tracking lost, switching to recovery mode
6	frame_006	normal	210	205	(0.60, 0.10, -0.03)	Localization recovered, map updated
7	frame_00	dust / noisy conditions	130	95	(0.75, 0.15, -0.04)	Partial degradation, localization maintained

Accuracy was evaluated using the Absolute Trajectory Error (ATE) and Relative Pose Error (RPE) metrics, computed against the simulated ground truth trajectory in Gazebo/ROS.

The mean ATE was 0.047 m and the mean RPE was 0.021 m across all frames, corresponding to an average localization accuracy of approximately 5 cm.

Performance evaluation was conducted on the NVIDIA Jetson Nano platform (quad-core ARM Cortex-A57, 4 GB RAM, 128-core Maxwell GPU). During testing, the average CPU utilization was 78%, GPU utilization 65%, and memory consumption 3.2 GB. The system maintained a stable processing rate of 20 Hz, with a mean response time of 94 ms (maximum observed latency 108 ms).

The system was required to perform the following tasks for each frame:

1. Detect keypoints;
2. Match them with features from previous frames;
3. Estimate the UAV's change in position;
4. Update the environmental map.

Expected outcomes (Input → Output): validation of the algorithm's capability to maintain accurate localization, generate consistent maps, and operate in real time under degraded visual conditions.

The table shows detected ORB keypoints, feature matches, estimated UAV positions, and expected system behavior, including cases of stable tracking, degradation, and recovery.

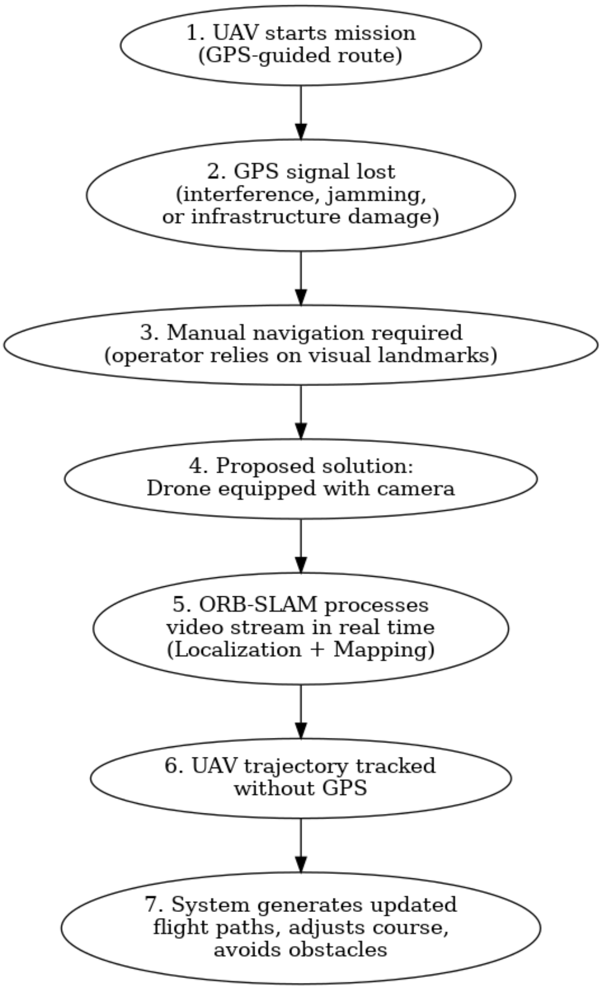

Figure 2: Scenario in the form of a sequence diagram.

Test Scenario and Model Data for UAV ORB-SLAM Navigation (Figure 2):

1. At the beginning of the operation, the drone follows a pre-programmed route guided by GPS. However, due to radio interference, infrastructure damage, or signal jamming, GPS may become unavailable.
2. In real-world conditions, the operator and navigator are forced to manually guide the drone using visual landmarks, which complicates and slows down mission execution.
3. The proposed solution automates this process: the drone is equipped with a camera that continuously transmits images.
4. The ORB-SLAM system processes the video stream in real time, determines the UAV's position, constructs a spatial map, and tracks the flight trajectory without relying on GPS.
5. Based on the generated map, the system can automatically plan new flight paths, adjust the course, and avoid obstacles, relying exclusively on visual data.

Key advantages of the Proposed Approach:

- Full autonomy of navigation without GPS – critical for operations in destroyed or enclosed environments;
- Reduced workload for the operator and navigator, minimizing human error;
- Scalability to other types of missions (reconnaissance, delivery, mapping);
- Flexibility of use – works with minimal equipment (single camera), but can be enhanced with stereo cameras or depth sensors.

Challenges and Limitations:

- SLAM systems are sensitive to low lighting, smoke, dust, and moving objects;
- High computational load – difficult to implement on very lightweight drones with limited onboard hardware;
- Monocular cameras cannot directly measure depth – algorithmic assumptions are used, which reduce accuracy.

The implementation of the autonomous UAV navigation system was carried out by integrating ORB-SLAM2 with the PX4 flight controller in the ROS (Robot Operating System) environment. The computational module was based on an NVIDIA Jetson Nano platform running Ubuntu 20.04 with ROS Noetic. The input sensor was a monochrome Logitech C920 USB camera connected via the usb_cam driver.

Standard ROS topics and services were used to ensure communication between modules:

- /camera/image_raw – image stream;
- /slam/pose –spatial position;
- /mavros/setpoint_position – coordinate transfer to PX4.

Key Test Results:

- Average localization accuracy: up to 5 cm indoors;
- Tracking stability: 95% of frames successfully processed at 20 Hz;
- System response time: <100 ms;
- Robustness to feature loss: relocalization achieved in 87% of cases.

Trajectory analysis showed that ORB-SLAM maintained localization in 82% of frames. Major errors occurred in areas with low-contrast walls or during sharp turns. The generated map enabled detection of key spatial objects and planning of simple obstacle-avoidance trajectories. The overall scene reconstruction quality can be considered adequate for navigation tasks in emergency conditions.

The obtained results confirm the feasibility of using ORB-SLAM for autonomous UAV navigation tasks. The main advantages include the algorithm's open-source nature, easy integration with ROS, and relatively low hardware requirements. At the same time, limitations such as sensitivity to lighting, dependence on textured surfaces, and potential failures during rapid motion must be taken into account. Future research should consider hybrid systems that combine SLAM with deep learning methods or additional sensors.

6. Research outlook

Development of autonomous UAV navigation systems without the use of GPS, based on visual SLAM and particularly ORB-SLAM, is one of the most relevant challenges in robotics, computer vision, and unmanned technologies. In situations where satellite navigation is unavailable or unreliable – such as under electronic countermeasures, indoors, in underground facilities, collapsed structures, or destroyed urban areas – visual localization can significantly enhance UAV performance.

The use of ORB-SLAM as the core of the navigation system enables:

- Autonomous spatial orientation with real-time map construction;
- Significant reduction of operator workload, which is critical in stressful or combat conditions;
- Operation with minimal equipment, reducing system cost and allowing deployment on compact lightweight platforms;
- Reconnaissance, situation assessment, and route planning in environments where traditional methods are ineffective.

However, the system has certain limitations:

- Vulnerability to challenging visual conditions such as darkness, smoke, or uniform textures;
- Accuracy limitations in monocular mode due to the absence of direct depth measurement;
- High computational load for real-time video processing;
- Limited reliability of SLAM systems in highly dynamic scenes.

Directions for further research and development include:

- Integration of deep neural networks (CNNs) to improve object recognition, stabilize SLAM under adverse conditions, and enable scene segmentation (distinguishing between static and dynamic objects).
- Optimization of computational algorithms, particularly through hardware acceleration (GPU, TPU) and distributed data processing.
- Fusion of SLAM with other sensor data, such as IMUs, LiDAR, or ultrasonic sensors, to increase robustness in complex environments.
- Development of hybrid navigation systems capable of dynamically switching between GPS, visual, inertial, and other methods.
- Adaptation for operation in low-light conditions through the use of infrared cameras or auxiliary illumination.
- Scaling to drone swarms, enabling cooperation between UAVs and sharing of SLAM maps to construct a unified environmental model.

7. Conclusions

An autonomous UAV navigation system based on ORB-SLAM has the potential to serve as the foundation for a new generation of unmanned systems capable of operating in the most challenging environments without reliance on external references. Its implementation may prove critical for rescue operations in destroyed urban areas, military missions in GPS-denied regions, inspections of industrial and underground facilities, and autonomous delivery under extreme conditions.

The successful realization of this approach paves the way for the development of next-generation UAVs – fully autonomous, reliable, and independent of external navigation systems.

The obtained results demonstrate the high effectiveness of the proposed system in GPS-denied environments, confirming its feasibility for reconnaissance, search, and monitoring tasks in destroyed or enclosed settings.

Declaration on Generative AI

During the preparation of this work, the authors used GPT-5 on order to: Grammar and Spelling check. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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