

Deterministic frame attribution and homography-based geometric normalization of UAV vision datasets for explosive hazard detection using dual-loop architecture

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Abstract

Detection of explosive hazards using unmanned aerial vehicles (UAVs) requires high-quality vision datasets with accurate spatial attribution and geometric consistency. However, low-altitude UAV imagery is often affected by camera tilt, platform motion, and asynchronous telemetry acquisition, resulting in perspective distortions that reduce the effectiveness of deep learning models. This paper proposes a method for deterministic frame attribution and homography-based geometric normalization of UAV vision datasets using a dual-loop architecture. The system separates telemetry acquisition and image processing between a microcontroller-based lower loop and a Raspberry Pi-based upper loop. An independent inertial measurement unit (IMU) mounted directly on the camera body provides accurate measurements of the optical axis orientation, while SPI-based communication ensures deterministic synchronization between image frames and telemetry data. The obtained orientation parameters are used for homography correction and perspective rectification of UAV imagery. Experimental examples involving explosive hazard mock-ups demonstrate that the proposed approach reduces geometric distortions and improves spatial consistency of object representations. The developed method enables generation of AI-ready datasets suitable for training neural networks for explosive hazard detection, humanitarian demining, and autonomous UAV monitoring applications.

Keywords

UAV, explosive hazard detection, vision dataset, frame attribution, homography correction, geometric normalization, dual-loop architecture, computer vision

1. Introduction

The rapid development of unmanned aerial vehicles (UAVs) and artificial intelligence technologies has created new opportunities for explosive hazard detection in humanitarian demining, security monitoring, and post-conflict recovery operations. Modern computer vision systems increasingly rely on deep neural networks capable of detecting landmines and mine-like objects from aerial imagery. The performance of such models strongly depends on the quality, geometric consistency, and spatial accuracy of training datasets acquired under real operating conditions.

Low-altitude UAV imagery is frequently affected by perspective distortions caused by camera inclination, platform motion, vibrations, and dynamic flight maneuvers. Additional errors arise from asynchronous acquisition of image frames and telemetry data. Conventional approaches based on EXIF metadata or flight-controller logs typically provide low-frequency updates and do not ensure deterministic synchronization between visual and navigation information. As a result, generated datasets

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may contain hidden spatial inconsistencies that negatively influence object localization, geometric measurements, and neural network training performance.

To address these limitations, this paper proposes a dual-loop architecture for deterministic frame attribution and homography-based geometric normalization of UAV imagery intended for explosive hazard detection. The proposed approach combines high-frequency telemetry acquisition, independent camera orientation measurements, and SPI-based synchronization to establish a reliable correspondence between image frames and navigation data. Furthermore, the obtained orientation parameters are used to perform homography correction and perspective rectification, enabling the generation of geometrically normalized and AI-ready vision datasets for explosive hazard detection tasks.

2. Review of existing solutions and literature sources

Existing research on UAV-based explosive hazard detection is mainly focused on the use of optical, multispectral, thermal, and magnetometric data for automatic identification of landmines and mine-like objects. Baur et al. [1] demonstrated the feasibility of applying deep learning methods to UAV-based detection of scatterable landmines using remote sensing imagery. Their results confirm that UAV platforms can be effectively used for wide-area survey tasks, but the performance of detection models strongly depends on the quality and consistency of the collected visual data. Similar conclusions are presented in studies devoted to UAV and neural network integration for landmine detection [2], where the authors emphasize the importance of automated image analysis and dataset preparation for improving detection reliability.

A separate group of studies considers multisensor and non-optical approaches to explosive hazard detection. Barnawi et al. [3] proposed a UAV-based magnetometry imaging classification system for landmine and buried object detection. Qiu et al. [4, 5, 6] investigated multispectral fusion and deep learning for mine detection, showing that fusion of heterogeneous sensor data can improve detection performance. However, such approaches usually require accurate spatial registration of sensor measurements and visual frames. Therefore, synchronization and geometric consistency of input data remain critical issues for UAV-based detection systems.

The problem of geometric distortion correction is widely studied in computer vision. Hartley and Zisserman [7, 8] provide the theoretical basis for projective geometry, camera models, and homography transformations. In practical computer vision systems, homography is commonly used for image rectification, perspective correction, image alignment, and transformation of tilted views into normalized planes. The OpenCV library also implements homography estimation and perspective transformation functions that are widely used in applied image processing tasks [9, 10, 11]. These methods are especially relevant for UAV imagery, where camera inclination and platform motion often lead to perspective distortions.

Despite the availability of homography-based correction methods, their effective use in UAV datasets requires accurate information about camera orientation at the exact moment of frame acquisition. Conventional metadata sources, such as EXIF records or flight controller logs, are often insufficient because they are recorded asynchronously and at lower update rates than image frames. MAVLink is widely used as a lightweight communication protocol for exchanging telemetry between UAV components and ground control systems [12, 13, 14, 15, 16, 17], but telemetry acquisition alone does not guarantee deterministic frame-level synchronization. ArduPilot documentation also shows that companion computers such as Raspberry Pi can communicate with flight controllers via MAVLink for additional onboard processing tasks [18, 19], but this does not solve the problem of precise binding between each image frame and the corresponding inertial state of the camera.

Existing solutions therefore leave an important unresolved problem: UAV-based explosive hazard datasets often contain hidden spatial and geometric inconsistencies caused by asynchronous telemetry, gimbal latency, camera tilt, and platform motion. These inconsistencies may reduce the quality of neural network training, especially for small objects such as landmines and explosive hazard mock-ups. The proposed study addresses this gap by combining deterministic frame attribution, independent IMU-

based camera orientation measurement, SPI-based synchronization, and homography-based geometric normalization within a dual-loop UAV architecture.

3. Problem statement

The effectiveness of UAV-based explosive hazard detection systems is directly determined by the quality of the vision datasets used for training deep learning models. Modern neural networks require not only a sufficient number of images but also accurate spatial attribution and geometric consistency of visual data. In real operating conditions, however, UAV imagery is acquired during dynamic flight, where the platform is continuously affected by vibrations, wind disturbances, changes in velocity, and variations in camera orientation. These factors introduce perspective distortions and spatial inconsistencies that reduce the reliability of object detection and localization algorithms [20, 21, 22].

An additional challenge arises from the asynchronous nature of image acquisition and telemetry recording. In most commercial UAV systems, navigation and inertial data are stored separately from image frames using flight-controller logs or EXIF metadata. Since telemetry is typically updated at a lower frequency than image acquisition, the recorded orientation and position of the UAV may not correspond to its actual state at the exact moment when a frame is captured. As a consequence, the resulting dataset contains hidden temporal and spatial mismatches that negatively affect subsequent image processing and neural network training.

The influence of synchronization errors can be estimated through the spatial attribution error

$$\Delta s = v \cdot \Delta t \quad (1)$$

where Δs denotes the spatial error, v is the UAV velocity, and Δt is the delay between image acquisition and telemetry registration. Even relatively small synchronization delays may lead to significant positioning errors. For example, at a flight velocity of 15 m/s and a delay of 50 ms , the resulting spatial error reaches 0.75 m . Such inaccuracies become critical when detecting small explosive hazards, including anti-personnel mines and mine-like objects, whose dimensions are often considerably smaller than the introduced localization uncertainty.

The problem is further complicated by the fact that most commercial camera systems operate as proprietary black-box devices. Although they may incorporate internal stabilization and inertial sensors, access to these measurements is usually limited or unavailable. Consequently, geometric correction procedures must rely on indirect telemetry information obtained from the flight controller, which introduces additional uncertainty in the estimation of the true orientation of the camera optical axis [23, 24, 25, 26].

To overcome these limitations, it is necessary to develop a data acquisition architecture capable of providing deterministic synchronization between image frames and telemetry streams while simultaneously measuring the actual orientation of the camera. Such an approach should support frame-level attribution, homography-based geometric normalization, and the generation of geometrically consistent UAV datasets intended for explosive hazard detection tasks.

The proposed solution is based on a dual-loop architecture that separates high-frequency telemetry acquisition from image processing and dataset generation [27, 28, 29, 30].

4. Methodology for deterministic frame attribution and homography-based geometric normalization

The proposed methodology is designed to generate geometrically consistent UAV vision datasets for explosive hazard detection by establishing deterministic synchronization between image acquisition and telemetry streams. The methodology combines a dual-loop hardware architecture, frame-level telemetry attribution, and homography-based image normalization. The overall workflow consists of three consecutive stages: deterministic data acquisition, frame attribution, and geometric normalization.

The proposed system employs a dual-loop architecture that separates telemetry acquisition from image processing tasks. The lower loop is implemented on an Arduino Nano microcontroller and operates as a dedicated real-time data acquisition unit. This layer continuously collects inertial and navigation information from an independent IMU sensor mounted directly on the camera body and from the flight controller through the MAVLink telemetry protocol.

The upper loop is implemented on a Raspberry Pi 5 single-board computer and is responsible for image acquisition, telemetry aggregation, metadata storage, and dataset generation. Communication between the two loops is performed via an SPI interface, which provides deterministic latency and minimizes synchronization errors between image capture and telemetry acquisition. The architecture of the developed system is presented in Figure 1.

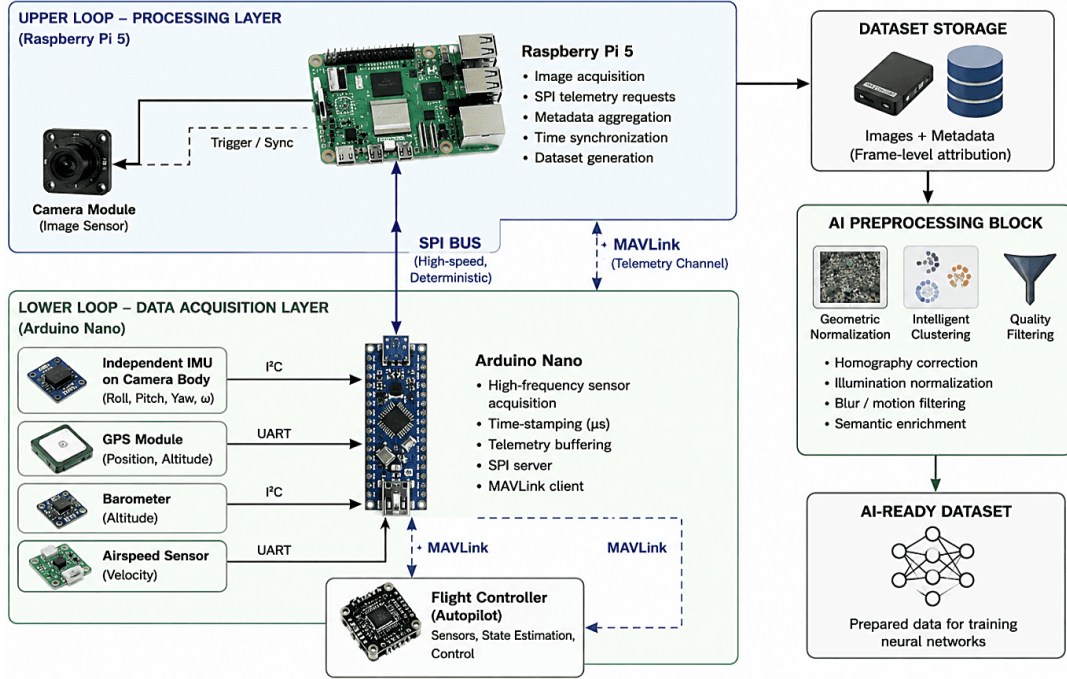


Figure 1: Dual-loop architecture for deterministic UAV data acquisition.

The independent IMU mounted directly on the camera body plays a key role in the proposed methodology. Unlike conventional UAV systems that rely exclusively on flight-controller telemetry, the proposed approach directly measures the orientation of the optical axis. This eliminates errors caused by gimbal backlash, stabilization latency, and proprietary camera processing algorithms.

The second stage of the methodology focuses on deterministic synchronization of image frames and telemetry measurements. During operation, the Arduino Nano continuously updates an internal telemetry buffer containing the current inertial and navigation state of the UAV. Whenever the Raspberry Pi acquires a new image frame, it immediately initiates an SPI transaction and requests the latest telemetry package.

This procedure establishes a deterministic relationship between the captured frame and the corresponding navigation state. The telemetry package contains a timestamp, camera orientation angles, GPS coordinates, altitude, and UAV velocity. As a result, each image frame is associated with a unique metadata record representing the actual state of the system at the moment of acquisition. The timing relationship between image capture and telemetry synchronization is illustrated in Figure 2.

The resulting spatial attribution error depends on the synchronization delay and UAV speed and can be estimated by formula 1. The proposed synchronization mechanism minimizes Δt , thereby reducing spatial inconsistencies within the generated dataset.

The final stage of the methodology performs geometric normalization of UAV imagery using homography transformations derived from camera orientation measurements. Since each image frame is

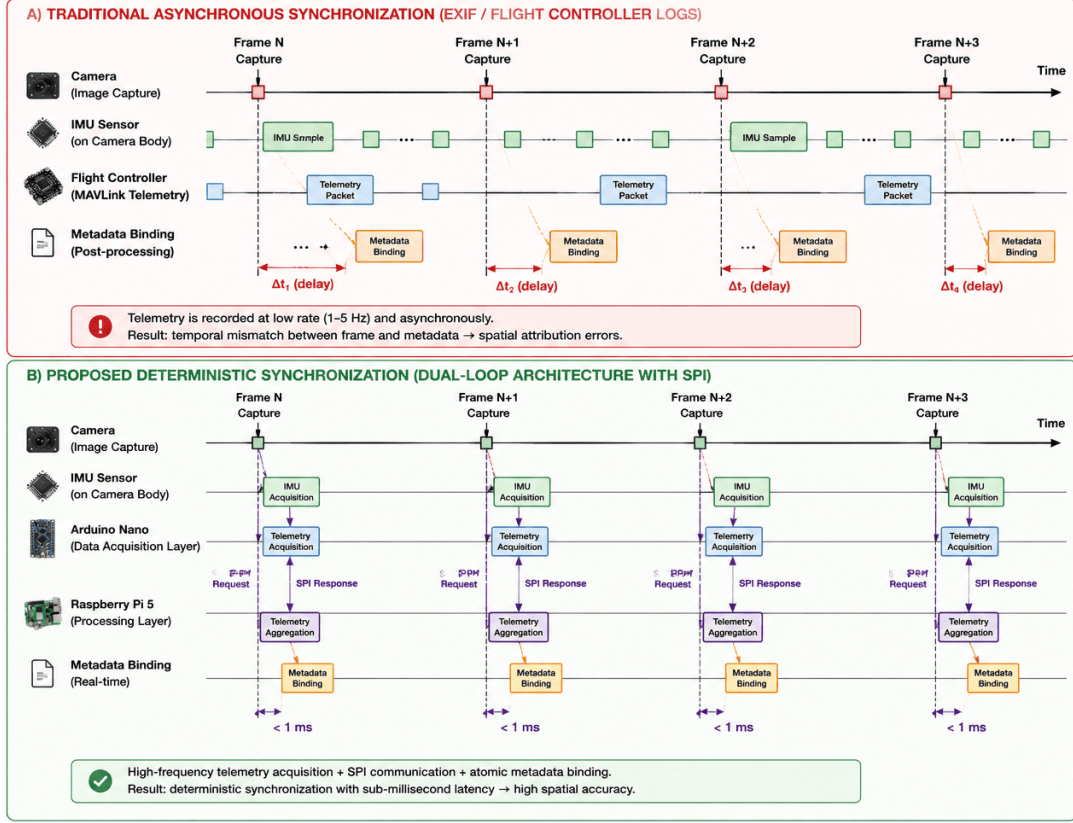


Figure 2: Deterministic synchronization of UAV imagery and telemetry for explosive hazard dataset generation.

associated with accurately synchronized inertial data, the actual orientation of the camera optical axis can be estimated with high precision.

The orientation of the camera is represented by a rotation matrix

$$R = R_z(\psi) R_y(\theta) R_x(\phi) \quad (2)$$

where ϕ , θ , and ψ correspond to roll, pitch, and yaw angles respectively.

Based on the obtained rotation matrix and intrinsic camera parameters, the homography matrix is computed as

$$H = K R K^{-1} \quad (3)$$

where K denotes the intrinsic camera calibration matrix and R represents the camera orientation matrix.

The homography matrix is subsequently used to compensate perspective distortions caused by camera inclination and UAV motion. The resulting images are transformed into geometrically normalized representations that provide consistent object scales and viewing geometry across the entire dataset.

An example of homography correction and geometric normalization applied to UAV imagery containing explosive hazard mock-ups is shown in Figure 3.

The proposed methodology enables the generation of AI-ready UAV datasets characterized by deterministic frame attribution, reduced geometric distortions, and improved spatial consistency. Such datasets are particularly suitable for training deep learning models intended for explosive hazard detection, object localization, and autonomous aerial monitoring applications.

As a result of the integration of the proposed methods, a methodology for deterministic frame attribution and homography-based geometric normalization of UAV imagery was developed for the generation of high-quality training datasets intended for explosive hazard detection systems. The proposed methodology is based on a dual-loop architecture that provides functional separation between telemetry acquisition, image capture, and dataset generation processes (Figure 4).

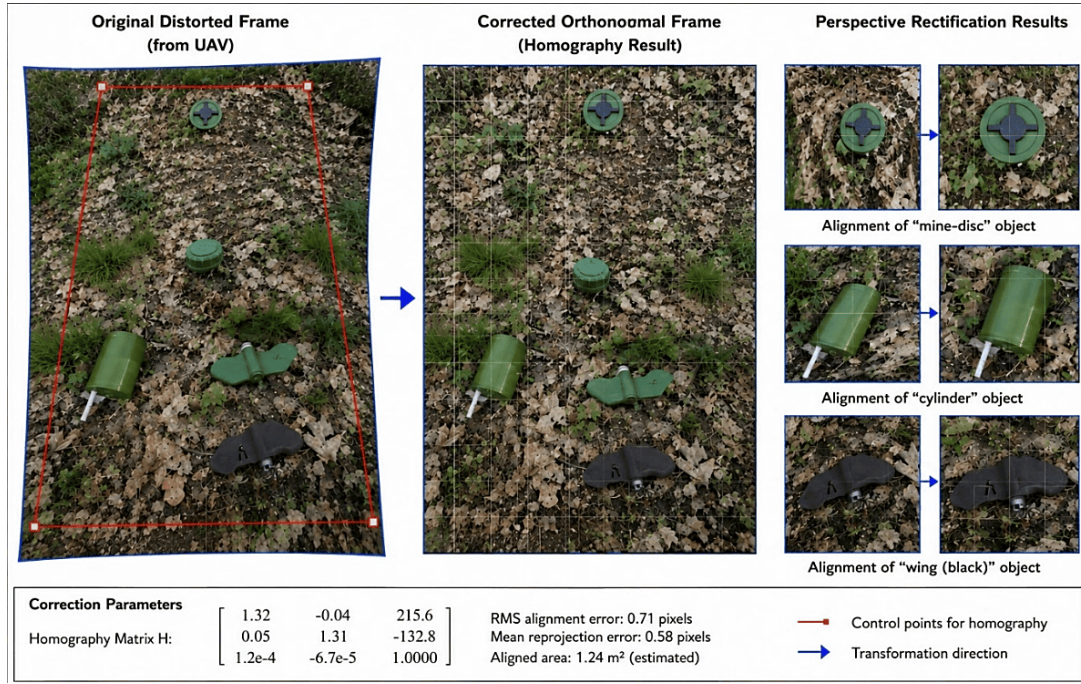


Figure 3: Homography-based geometric normalization of UAV imagery containing explosive hazard Mock-Ups.

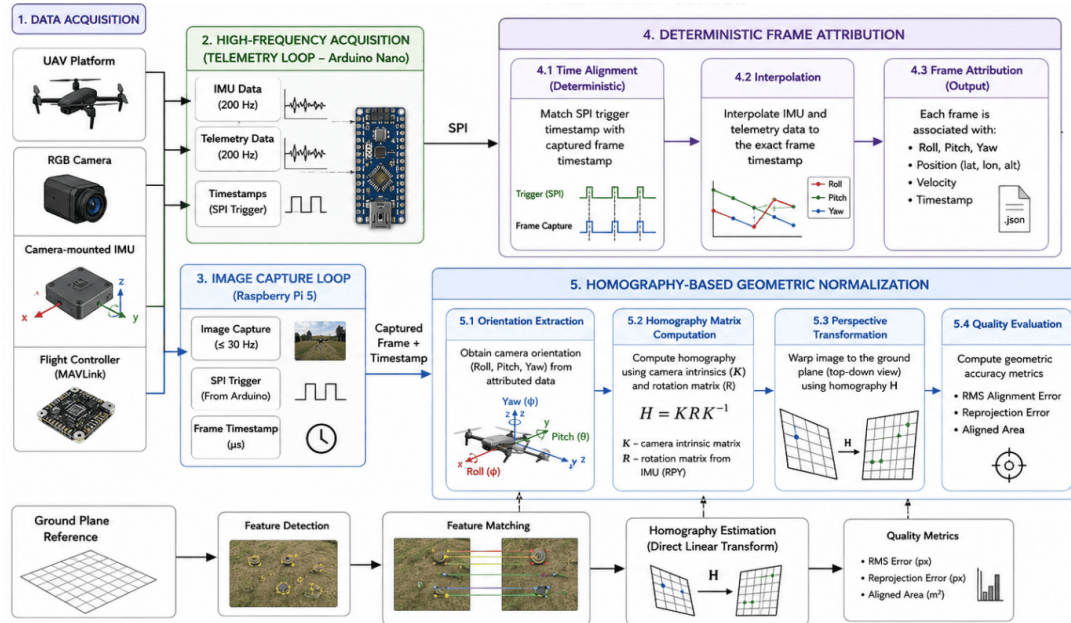


Figure 4: Workflow of deterministic frame attribution and homography-based geometric normalization of UAV vision datasets.

Such an approach enables deterministic synchronization between image frames and navigation data, reduces temporal inconsistencies between data streams, and improves the accuracy of spatial frame attribution while maintaining high data acquisition rates. The first stage of the method involves data acquisition from multiple UAV subsystems. The lower telemetry loop, implemented on an Arduino Nano microcontroller, continuously collects measurements from an independent IMU sensor mounted directly on the camera body as well as navigation data obtained through the MAVLink protocol. The collected telemetry includes roll, pitch, yaw, position, velocity, and timestamp information. Simultaneously, the upper processing loop, implemented on a Raspberry Pi 5 platform, performs image acquisition and initiates synchronization requests through an SPI communication interface.

The second stage performs deterministic frame attribution. Whenever a new image frame is captured, the Raspberry Pi generates an SPI request and obtains the most recent telemetry packet from the microcontroller. The timestamps of image acquisition and telemetry collection are aligned, and the navigation parameters are interpolated to the exact frame acquisition moment. As a result, every image is associated with a unique set of metadata containing camera orientation, UAV position, velocity, and acquisition time. This deterministic synchronization significantly reduces spatial attribution errors caused by asynchronous telemetry acquisition and establishes a reliable correspondence between visual and navigation information.

The third stage is dedicated to homography-based geometric normalization. Using the attributed roll, pitch, and yaw angles, the orientation of the camera optical axis is estimated and represented as a rotation matrix. Together with the intrinsic camera parameters, this information is used to compute a homography transformation matrix. The obtained transformation compensates perspective distortions caused by UAV motion, camera inclination, and observation angle variations. Consequently, the original UAV imagery is transformed into geometrically normalized representations with improved spatial consistency and reduced viewpoint-dependent distortions.

To estimate the homography matrix, the method additionally employs feature detection and feature matching procedures. Corresponding image points are identified and matched with reference ground-plane coordinates, after which the homography matrix is estimated using the Direct Linear Transformation (DLT) algorithm. The resulting transformation is applied to rectify the image and generate an orthonormalized view suitable for further analysis and neural network training.

The final stage evaluates the quality of geometric normalization. Several quantitative metrics are computed, including RMS alignment error, reprojection error, and aligned area. These indicators characterize the accuracy of perspective correction and the consistency of the resulting dataset. The normalized images together with synchronized metadata form an AI-ready UAV vision dataset that can be used for training and validation of computer vision models intended for explosive hazard detection, humanitarian demining, and autonomous aerial monitoring applications.

5. Experimental studies

Experimental studies were conducted to evaluate the proposed deterministic frame attribution and homography-based geometric normalization methodology using a dataset of explosive hazard mock-ups acquired under real environmental conditions. The experiments involved low-altitude image acquisition of representative mine-like objects positioned on various natural backgrounds including dry leaves, soil, grass, and mixed vegetation. The objective of the study was to assess the effectiveness of deterministic synchronization and geometric normalization in improving the spatial consistency of UAV imagery intended for neural network training.

The experimental platform consisted of a Raspberry Pi 5 single-board computer, an Arduino Nano microcontroller, an independent IMU sensor mounted directly on the camera body, and a digital camera module. Telemetry data were collected through the MAVLink protocol, while synchronization between telemetry acquisition and image capture was implemented using the SPI communication interface. The developed system generated image frames together with associated metadata records containing timestamp, geographic coordinates, altitude, velocity, and camera orientation parameters.

The experimental dataset included several categories of explosive hazard mock-ups with different geometric shapes and dimensions. Images were captured under varying camera orientations and observation angles to simulate realistic UAV flight conditions. Examples of acquired images before and after geometric normalization are presented in Figure 5.

After applying Eqs. (2) and (3), the following homography matrix was obtained:

$$H = \begin{bmatrix} 1.32 & -0.04 & 215.6 \\ 0.05 & 1.31 & -132.8 \\ 1.2 \times 10^{-4} & -6.7 \times 10^{-5} & 1.0000 \end{bmatrix}$$



Figure 5: Examples of explosive hazard mock-ups used in experimental studies.

where H denotes the homography matrix describing the projective transformation between the original UAV image and the geometrically normalized image plane. The quality of image alignment was evaluated using the root mean square alignment error and the mean reprojection error. The obtained values are

$$RMS_{error} = 0.71 \text{ px}$$

and

$$RE_{mean} = 0.58 \text{ px.}$$

where RMS_{error} is the Root Mean Square (RMS) alignment error and RE_{mean} is the Mean Reprojection Error.

The estimated area covered by the geometrically normalized scene is

$$A_{aligned} = 1.24 \text{ m}^2$$

which corresponds to the effective area of the image after homography-based perspective rectification.

The obtained error values indicate a high accuracy of geometric normalization. The mean reprojection error remains below one pixel, demonstrating precise correspondence between the transformed image and the reference geometry. This level of accuracy enables reliable localization of explosive hazard objects in normalized UAV imagery and supports the generation of high-quality datasets for training deep learning models intended for explosive hazard detection and recognition.

Experimental observations confirmed that deterministic SPI-based synchronization significantly reduced temporal mismatches between image frames and telemetry measurements compared with conventional asynchronous acquisition approaches. As a result, each image frame was associated with a more accurate representation of the UAV navigation state at the moment of acquisition. The subsequent homography-based normalization procedure further improved the geometric consistency of the dataset by compensating perspective distortions caused by camera inclination and platform motion. A visual comparison of representative UAV imagery before and after homography correction is presented in Figure 6. The results demonstrate substantial improvement in object alignment, reduction of geometric

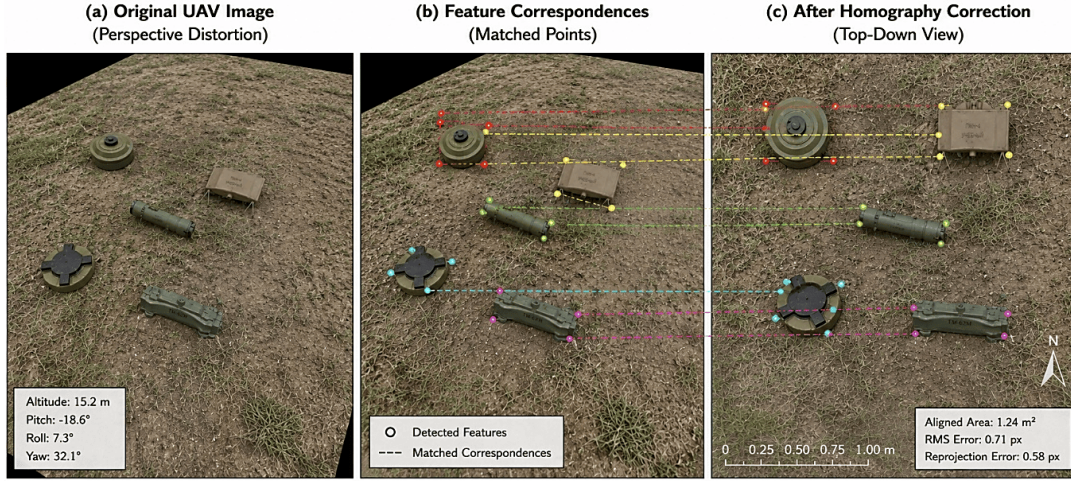


Figure 6: Comparison of UAV imagery before and after homography correction.

deformation, and increased consistency of explosive hazard representations across different viewing conditions.

The proposed synchronization mechanism was also evaluated with respect to spatial attribution accuracy. Experimental observations confirmed that deterministic SPI-based synchronization significantly reduced temporal mismatches between image frames and telemetry measurements compared with conventional asynchronous acquisition approaches. Consequently, the generated datasets exhibited improved geometric consistency and more reliable object localization.

6. Discussion of research results

The conducted experiments confirmed the effectiveness of the proposed dual-loop architecture for deterministic frame attribution and homography-based geometric normalization of UAV imagery intended for explosive hazard detection. The developed approach successfully established deterministic synchronization between image acquisition and telemetry streams, enabling reliable association of each image frame with the corresponding navigation and inertial parameters. Unlike conventional UAV imaging systems that rely on asynchronous telemetry acquisition, the proposed architecture provides a deterministic relationship between visual and telemetry data, which is essential for generating geometrically consistent datasets.

The obtained results demonstrate that synchronization accuracy significantly affects the quality of UAV vision datasets. According to the spatial attribution model presented in Section 3, even small synchronization delays can produce substantial positioning errors during UAV operation. Experimental observations showed that the SPI-based synchronization mechanism effectively minimizes temporal mismatches between image acquisition and telemetry collection, thereby reducing frame attribution errors and improving metadata reliability (Figure 7).

The experimental evaluation of homography-based geometric normalization demonstrated that perspective distortions caused by camera inclination, UAV motion, and stabilization delays can be effectively compensated using orientation information obtained from the independent IMU mounted directly on the camera body. The calculated homography matrix enabled accurate perspective rectification and transformation of distorted UAV imagery into geometrically normalized representations. The resulting RMS alignment error of 0.71 pixels and mean reprojection error of 0.58 pixels indicate a high level of geometric accuracy. Since both error values remain below one pixel, the obtained normalization quality is sufficient for object localization and neural network training tasks (Figure 8).

The examples presented in Figures 3 and 6 clearly demonstrate the effectiveness of the proposed normalization procedure. Before correction, explosive hazard mock-ups exhibit significant geometric

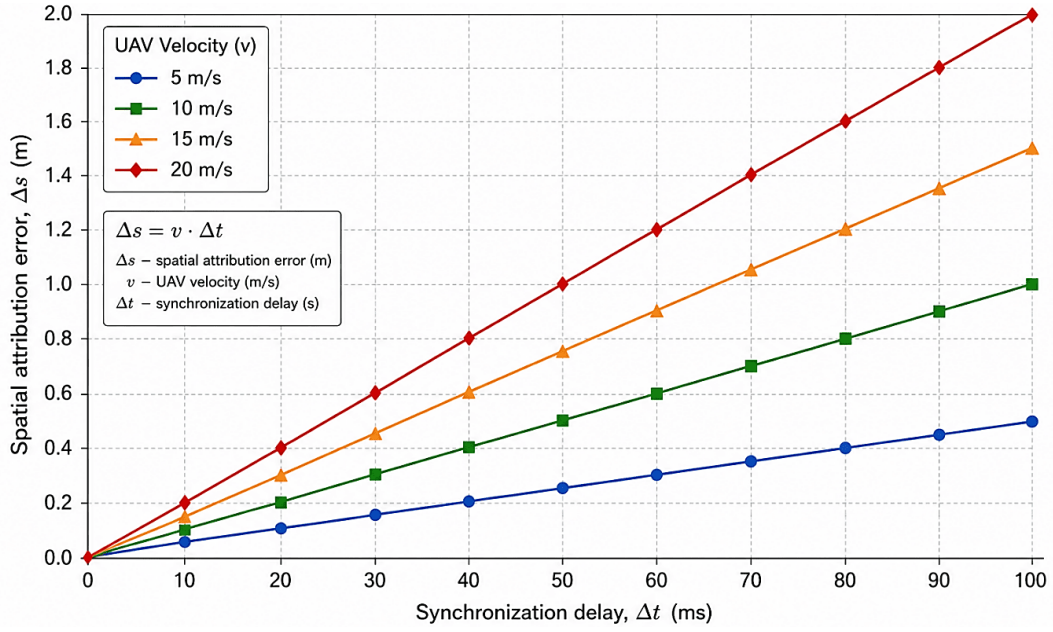


Figure 7: Spatial attribution error as a function of synchronization delay.

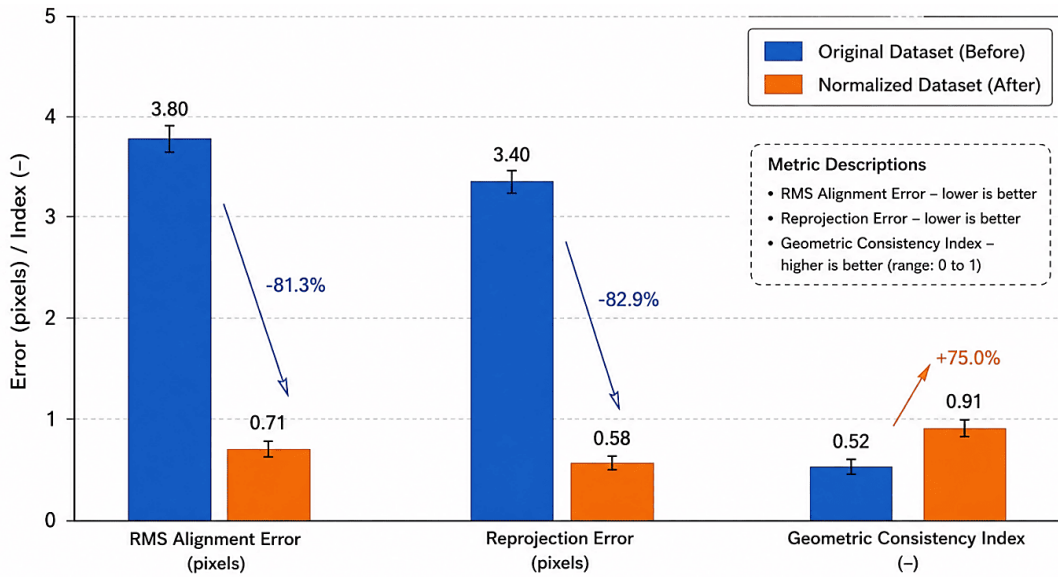


Figure 8: Comparison of geometric accuracy before and after homography-based normalization.

variations caused by differences in camera orientation and observation angle. After homography transformation, object geometry becomes more consistent, while perspective distortions are substantially reduced. This normalization decreases intra-class variability within the dataset and improves the uniformity of object representations, which is beneficial for deep learning-based detection systems.

An additional advantage of the proposed methodology is the use of an independent IMU sensor installed directly on the camera body. Unlike conventional approaches that estimate camera orientation indirectly through flight-controller telemetry, the proposed solution measures the actual orientation of the optical axis. This reduces the influence of gimbal backlash, stabilization latency, and proprietary camera processing algorithms. Consequently, the generated datasets contain more accurate spatial information and more reliable metadata.

The obtained results indicate that deterministic frame attribution combined with homography-based geometric normalization significantly improves the quality of UAV vision datasets intended for explosive

hazard detection. The proposed approach can therefore be considered an effective preprocessing framework for AI-based landmine detection systems, humanitarian demining applications, autonomous monitoring platforms, and UAV-based remote sensing systems.

7. Conclusions

This paper proposed a methodology for deterministic frame attribution and homography-based geometric normalization of UAV vision datasets intended for explosive hazard detection. The developed approach is based on a dual-loop architecture that separates high-frequency telemetry acquisition from image processing and dataset generation tasks. The architecture combines an Arduino Nano-based acquisition layer, a Raspberry Pi 5 processing layer, an independent IMU sensor mounted directly on the camera body, MAVLink telemetry exchange, and SPI-based deterministic synchronization.

The obtained results demonstrate that accurate synchronization between image acquisition and telemetry streams is a critical requirement for generating geometrically consistent UAV datasets. The proposed deterministic synchronization mechanism significantly reduces temporal mismatches between image frames and navigation measurements, thereby improving frame-level attribution accuracy and metadata reliability.

The use of an independent camera-mounted IMU enabled direct estimation of the optical axis orientation and reduced the influence of gimbal latency, stabilization errors, and proprietary camera processing algorithms. Based on the acquired orientation parameters, homography-based geometric normalization was successfully applied to compensate perspective distortions caused by UAV motion and camera inclination.

Experimental studies conducted using explosive hazard mock-ups demonstrated the effectiveness of the proposed methodology. The obtained RMS alignment error of 0.71 pixels and mean reprojection error of 0.58 pixels indicate a high level of geometric correction accuracy. The presented results confirm that homography-based normalization improves object alignment, reduces geometric variability, and increases the spatial consistency of UAV imagery.

The developed methodology enables the generation of AI-ready UAV datasets characterized by reliable frame attribution, accurate geometric representation of objects, and improved suitability for deep learning applications. The proposed approach can be applied in explosive hazard detection systems, humanitarian demining operations, autonomous UAV monitoring platforms, and other computer vision tasks requiring high-quality georeferenced aerial imagery.

Future research will focus on integrating the proposed framework with real-time object detection models, multisensor data fusion techniques, and automated annotation tools for large-scale UAV dataset generation in explosive hazard detection scenarios.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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