

# Implementation of a Spatio-Temporal Data Registration System for Real-time Monitoring of Surface Defects in Nuclear Power Plant Structures using Multi-sensor UAVs

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## 1. Introduction

The usage of unmanned aerial vehicles (UAVs) for remote inspection of SOC structures is widely adapted to assess the structural health condition for large concrete facilities, such as nuclear power plant (NPP) containment buildings. While previous studies propose coupling UAVs with a deep learning model for automated condition assessments [1], these approaches predominantly require off-line *post*-processing from the obtained images. However, this extra process on post-flight data analysis hinders *on*-site real time decision and rapid response. Accurately diagnosing fine cracks and leaks on concrete surfaces requires analyzing diverse data sources, such as visual data and infrared (IR) thermal imaging [2].

Recent on-board edge computing and the integration of flight control systems with deep learning have laid the groundwork for real-time remote diagnostics [3-4]. Based on these approaches, we propose a new real-time integrated monitoring framework which combines a commercial UAV platform and a hybrid communication network. This system has been suggested to transmit complex, in-flight sensor data with low latency and perform precise spatio-temporal data registration for both image and IR data analysis.

## 2. Integrated Monitoring System Configuration

The proposed system consists of two main components, 1) hardware layers for multi-sensor data collection and 2) network layers for real-time transmission shown in Fig. 1. A DJI Matrice 300 RTK was selected as the base UAV platform in this study, carrying a high-resolution visual camera (Zenmuse H-20) and a dual IR thermal camera (FLIR Vue TZ20). To capture a broader range of environmental condition data from a nuclear power plant, radiation sensor and temperature/humidity sensors were integrated. These secondary sensors are controlled via an Arduino interface and processed by an onboard edge computing system (Jetson Orin-NX) mounted directly on the UAV, allowing continuous, localized data acquisition during flight.

To minimize data transmission latency, a hybrid communication network was designed. The wireless video downlink between the drone and the remote

controller (RC) relies on DJI's OcuSync for stable, low-latency transmission of high-definition (HD) video data and control signals. A wired connection is then used between the RC and the control tablet to prevent local data bottlenecks. On a broader scale, a Wire Guard-based virtual private network (Tailscale VPN) links the distributed nodes—the *on*-board edge computer, the control tablet (running the MSDK application), and the main PC (running the GUI)—across various physical networks such as LTE/5G and Wi-Fi network. It provides a single-logical IP band, ensuring secure *end-to-end* connectivity and reducing the risk of data loss regardless of the physical distance between the drone and the ground station.

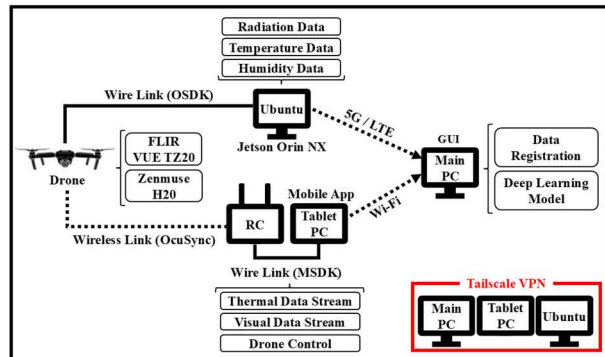


Fig. 1. Hardware configuration and hybrid network architecture of the proposed UAM based monitoring system.

## 3. Real-time Data Registration and Processing

Rather than physically overlaying pixels, this study registers multi-sensor data through precise spatio-temporal synchronization. The main PC's GUI time-aligns the high-precision RTK-GPS 3D coordinates (retrieved from the MSDK server), flight telemetry, and the visual and raw thermal video streams. Because the visual stream natively embeds MSDK On-Screen Display (OSD) metrics, operators can intuitively monitor real-time flight parameters like adaptive coordinates (RTK/GNSS), positioning status, battery life, and obstacle radar, shown in Fig. 2. This 'Synchronized Dual-view' setup allows complex, multi-sensor data to be compared instantly without visual clutter.

A dedicated control panel, in Fig. 3, centralizes the system's operation, integrating network status, flight



Fig. 2. Detailed view of the visual streaming interface with native MSDK OSD widgets, displaying essential flight metrics and adaptive navigation data.

controls, sensor monitoring, and You Only Look Once (YOLO) inference settings. To efficiently manage flight streaming data and track defects, an ‘Event-Triggered Archiving’ pipeline was developed. When the YOLO model detects specific anomalies in the thermal stream, it automatically triggers a recording of the entire GUI screen for 5-10 seconds immediately following the detection. These logs promptly appear in the ‘Event Archive’. By saving visual data alongside critical metadata—such as radiation levels, RTK coordinates, and ambient temperature and humidity values—these recordings serve as direct on-site evidence. This preserves the precise spatial and environmental context of the detected anomalies, eliminating the need for complex post-flight data mapping and allowing for immediate on-site evaluation.



Fig. 3. Detailed functional layout of the control panel, illustrating components for network status, flight control, real-time sensor monitoring, inference settings, and event archiving.

#### 4. System Implementation and Verification

The proposed framework was validated using a custom Python-based GUI to test real-time data transmission and processing. End-to-end latency—measured from the camera input to the GUI output—averaged roughly 225 ms ( $\pm 25$  ms). This confirms that visual and thermal streams, telemetry, and multi-sensor data can be displayed simultaneously without noticeable delay or data loss (Fig. 4). This low latency is crucial for maintaining an operator's situational awareness and ensuring safe flight control during live drone inspections near massive structures.



Fig. 4. Designed real time monitoring layout of the integrated monitoring GUI, simultaneously displaying (a) visual streaming, (b) thermal streaming, and (c) the control panel.

The YOLO-based inference pipeline was also rigorously tested under lossless thermal streaming conditions. The object detection algorithm processed the in-flight thermal data continuously without dropping frames, confirming that the ‘Event-Triggered Archiving’ mechanism works effectively in practice. Utilizing raw, lossless thermal data is highly advantageous, as it ensures that subtle temperature gradients—often indicative of fine cracks or internal leaks—are preserved and can be fed directly into the detection algorithm. Although the final recording module is still awaiting a fully trained defect detection model, the real-time inference pipeline's structural validity is verified. Once a model trained specifically on concrete cracks and leaks is deployed, the system will evolve from a simple monitoring tool into an automated, on-site diagnostic and recording solution.

#### 5. Conclusions

We successfully demonstrated a real-time integrated monitoring system for NPP exterior wall inspections by combining a UAV, multiple sensors, and a hybrid communication network. By achieving spatio-temporal data registration with a low latency of approximately 200ms, the system overcomes the limitations of offline post-processing, enabling rapid on-site diagnosis and response. Based on the developed monitoring system for early detection of abnormal outer concrete wall structure

by defect formations, we can monitor and evaluate the health condition of SOC structural surfaces, such as NPP wall and road conditions. Future work will focus on upgrading this framework into a fully automated structural safety diagnostic solution by integrating deep learning models specifically trained to detect concrete cracks and leaks.

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