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A Distributed Edge–Cloud Computing Framework for Multi-Unmanned System Coordination and Payload Processing

Patrick O'Connor[1*], Grace Murphy[1], Niamh Walsh[2], Eoin Byrne[3]

Abstract

Multi-unmanned systems are chiefly composed of unmanned vehicles, aerial drones, multi-legged robots, and comparable unmanned robotic systems. Through the unification and harmonized functioning of these robotic devices, collaborative multi-mission execution and self-directed operations across varied settings can be realized. Within the domain of surveying and mapping, the established method of data gathering using a single type of unmanned equipment is no longer adequate to meet acquisition requirements in complex spatial contexts (e.g., low-altitude, terrestrial, interior, subterranean, and similar). When addressing the data-capture needs of complex spaces, deploying distinct robot categories for cooperative work is a crucial strategy to boost task efficiency. Additionally, the inherently constrained computational and storage resources of unmanned systems pose considerable challenges for multi-unmanned configurations. Consequently, this paper proposes an edge–end–cloud fused multi-unmanned system payload management and computing platform (IMUC) that unites edge, endpoint, and cloud computing. By harnessing the enormous processing power and storage capacity of the cloud, the platform enables cloud-driven online task management and data capture visualization for multi-unmanned systems. The platform handles the complex intricacy of executing missions across diverse settings by weighing variables such as spatial factors, temporal constraints, and assignment fulfilment. It performs data-gathering operations at the endpoint, streamlines processing at the edge, and subsequently conveys the data to the cloud for visual rendering. The platform fluidly integrates edge processing, terminal hardware, and cloud resources, enabling effective resource allocation and distributed execution of computational tasks. Experimental findings show that the platform can competently execute the full sequence of payload supervision and computation for multi-unmanned systems under complex conditions. The platform delivers low latency and produces accurate routing outputs, significantly increasing fieldwork productivity. These evaluation outcomes confirm the platform's functionality and trustworthiness, providing a new approach to efficient multi-unmanned-system workflows for surveying and mapping applications and linking cloud computing to the realization of intelligent urban environments.

Keywords Digital twins, Multi-unmanned systems, Payload management, Cloud platform, Multi-machine collaboration, Edge–device–cloud integration

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Introduction

Over recent years, unmanned systems, as a transformative technical modality, have been gradually reshaping everyday existence and possess the capability to overhaul commercial and industrial domains. Spanning from intelligent farming to

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smart supply chains, from airborne drones to self-driving vehicles, unmanned systems have spread across numerous sectors and are becoming indispensable tools for tackling tangible problems. The gathering of three-dimensional spatial information via unmanned platforms has become a highly investigated subject. Unmanned devices deliver benefits including maneuverability, enhanced precision, strong environmental compatibility, and broad acquisition coverage, markedly improving the accuracy and efficiency of surveying and mapping operations and steadily shifting surveying operations from human-operated to unmanned. Separate categories of unmanned systems and surveying conditions place differing expectations on ground station capabilities, particularly regarding processing power. Legacy integration paradigms struggle to meet the demands of distributed, high-performance computation. On the one hand, large-scale ground station configurations are commonly set up on specialized machines with limited mobility and substantial maintenance costs. When processing capability falls short of task requirements, the fix is usually to supplement hardware. On the flip side, standard ground station gear can control only a single unmanned unit at a time, which does not support coordinated activity across multiple unmanned systems.

With the advancement of cloud computing and web-based technologies, many applications that require substantial processing power have moved to cloud infrastructure. This both cuts hardware outlays and satisfies the varying computational needs of distinct task settings. Cloud computing is an all-encompassing tech stack that combines virtualization, large-scale data handling, and communication, providing processing power and diverse services to endpoints via cloud servers [1]. Edge computing is centered on relocating processing and data handling toward the network periphery, enabling faster response and data processing [2]. The endpoint serves as the junction linking the tangible and digital spheres, which, in the context of unmanned systems, signifies an unmanned machine equipped with perception, data capture, and instantaneous response faculties. The amalgamation of edge–end–cloud aligns edge computation, terminal devices, and cloud processing to achieve efficient information processing and computational resource governance [3]. Edge units, functioning as peripheral nodes, can rapidly handle and filter data, forwarding essential information to the cloud for deeper scrutiny and manipulation. The cloud, conversely, delivers formidable processing power and storage resources capable of tackling large datasets and complex computational tasks. Endpoint machines fulfill roles in data acquisition and live response. The edge–end–cloud integrated paradigm opens up expansive implementation opportunities across numerous industries, enabling real-time data analysis and more informed decision-making.

The joint operation of multiple unmanned systems has become a vital direction in robotics [4]. Multi-unmanned configurations, via the cooperation of numerous intelligent entities, can complete elaborate assignments that a lone intelligent entity cannot manage alone. They are widely deployed in defense [5], rescue missions [6], cultivation [7], and other areas. The bulk of unmanned setups consists of uniform intelligent entities, whose individual capabilities limit the collective potential. However, multi-unmanned assemblies that combine different entity types offer advantages when tackling specific missions. For example, a multi-unmanned configuration combining aerial drones and terrestrial unmanned vehicles can expand the ground vehicle's field of view.

In contrast, the ground vehicle can reduce the drones' spatial constraints, enabling more complex tasks. Zhao and Li [8] presented a dynamic, joint-task-distribution framework for dissimilar unmanned platforms and explored the challenge of assigning tasks. The trial results indicated that the authors' hybrid refined algorithm, Hy-CAN, successfully increased system throughput. Zhou *et al.* [9] assembled a team of unmanned systems to investigate complex settings, and their study revealed that, through optimization procedures and joint control methods, a swarm of drones can achieve effective and stable cooperative work. Stolfi *et al.* [10] proposed an original mobile surveillance scheme, CROMM-MS, to patrol and detect individuals leaving confined zones. This scheme resolves the cooperative operation puzzle among diverse unmanned systems (UAVs, UGVs, and UMVs) and has shown encouraging results in tests. The preceding cases adequately demonstrate that the deficiencies of a standalone unmanned system can be remedied via cooperation among several unmanned systems.

The merging and depiction of multi-origin data across unmanned systems for mapping and measurement have been successful in real-world settings. Potena *et al.* [11] deployed aerial drones and ground vehicles in chart generation for

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precision cultivation. The drone's visual sensor captured images of the cropland, yielding a two-dimensional chart, whereas the ground vehicle captured imagery among the plants, yielding detailed cropland data. The research group developed an efficient methodology to merge datasets from drones and ground vehicles, resulting in a faithful three-dimensional map of the terrain and vegetation. Tagarakis *et al.* [12] used unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) for orchard mapping. They merged the outputs from airborne and surface mapping setups to deliver the most accurate portrayal of trees. Likewise, Asadi *et al.* [13] engaged multiple unmanned configurations for information acquisition on building sites. Their unmanned assemblies demonstrated collaborative pathfinding and map-making capabilities in enclosed, intricate settings. Multi-unmanned configurations have demonstrated numerous successful applications in cooperative mapping and measurement. Yet numerous challenges persist regarding the accuracy of test outcomes, warranting further investigation.

Currently, investigations into cloud-enabled management of unmanned systems largely focus on a single category, leaving scope for research into supervising multiple unmanned system types. Pino *et al.* [14] unveiled a cloud framework that marries drones with a cloud system for precision agriculture and airborne charting. This framework supports bidirectional interaction with multiple drones. Koubaa *et al.* [15] engineered a drone monitoring mechanism, DroneTrack, in which the cloud system calls upon drones to pursue mobile targets. Test findings revealed that DroneTrack achieved a mean tracking precision of 3.5 m for leisurely-moving targets. DJI, an enterprise headquartered in Shenzhen, has launched the DJI FlightHub 2 cloud system [16]. They scrutinized an all-in-one cloud platform for UAV assignment governance to realize full-scope, instantaneous situational consciousness. Nanjing Dayi Innovation Technology has crafted a cloud system for tethered drones [17], facilitating live oversight, trajectory scheduling, and drone data warehousing governance. These platforms have accomplished operational control of a solitary type of unmanned device. However, when undertaking multi-drone operations in intricate environments, a reliable and effective governance platform remains absent.

To address the challenges described above, we devised an intelligent service framework that brings together numerous capabilities, encompassing payload oversight for multi-unmanned configurations, scene information gathering management, live tracking, and real-time presentation of unmanned apparatus video streams, web-based manipulation and visual rendering of multi-sensor information, together with warehousing and examination of extensive data volumes. This framework effectively performs a range of data-gathering tasks for multi-unmanned systems in complex environments, addressing the challenges inherent in directing multiple unmanned systems. It is distinguished by its accessible interface and robust feature set, and it substantially boosts the self-sufficiency and smart operation of unmanned apparatus management.

Platform Architecture

As depicted in **Figure 1**, the holistic structure of IMUC is organized into the three subsequent strata: (i) Device stratum, which encompasses the networked hardware of diverse unmanned systems (such as ground-based unmanned vehicles, aerial drones, and the like). Each unmanned unit carries an onboard microcomputer (for instantaneous computational demands and communication with the cloud), sensing apparatus (affixed to unmanned units for gathering spatial environmental information, with distinct sensors applied depending on the task context), and a maneuvering platform (employed to direct the locomotion of unmanned systems). (ii) Transmission stratum, which permits fluid information passage between the cloud stratum and the device stratum. This stratum applies ROS Bridge and MQTT (Message Queuing Telemetry Transport) communication rules, with JSON and XML as the primary data formats. (iii) Cloud stratum, which delivers a suite of functionalities and modular units within a cloud computation setting. This covers dispersed processing, cloud retention, cloud functional modules, and interface engineering. These modules and functionalities leverage the cloud foundation to deliver extensive compute and storage capacity, catering to user needs for greater performance, scalability, and reliability.

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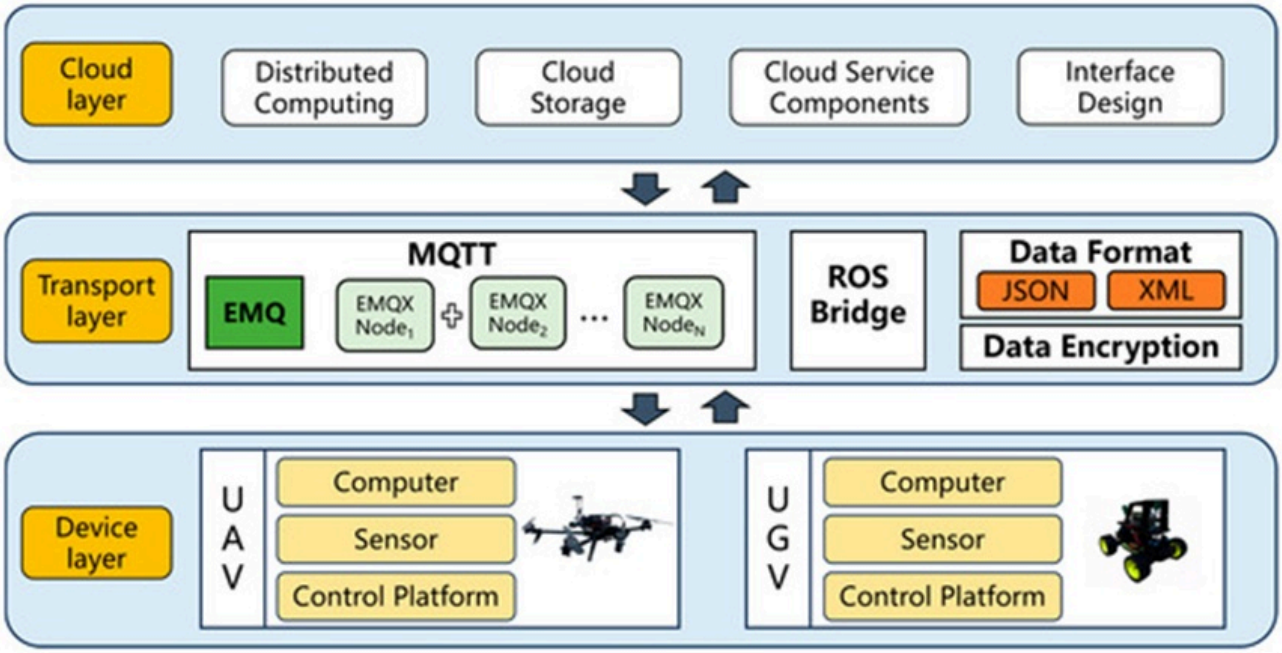

Figure 1. Platform architecture diagram.

The text that follows unpacks each stratum of the platform.

Device stratum

The device stratum is predominantly composed of unmanned apparatus that perform information-capture roles, including widely used unmanned aerial systems, ground-based unmanned systems, and analogous devices. These unmanned units are capable of carrying out missions dispatched from the cloud foundation, such as spatial information capture and object tracking. This stratum interconnects various network entities and utilities and relies on wireless networking to interface with the cloud foundation. It acquires command directives issued by the foundation and performs the related actions. The robot operating system (ROS) is widely adopted as a bridging framework for building robot programs and represents a key advancement in component-based software development for robots [18]. In an era when unmanned systems are widely used, the convergence of unmanned systems with the Internet of Things (IoT) ecosystem has made remote control remarkably straightforward [19, 20].

Transport stratum

The conveyance stratum is responsible for moving information between the device stratum and the cloud stratum, as well as for network supervision and resource allocation. The cloud stratum can send mission-specified directives to the numerous unmanned systems located in the device stratum via the conveyance stratum, a process enabled through internet protocol-driven interface modules. Moreover, network connectivity is indispensable for forwarding information from unmanned machines to the cloud, enabling smoother transport compared to older communication techniques such as telemetry radio channels. In this paper, the MQTT (Message Queuing Telemetry Transport) and ROSBridge communication protocols form the backbone. MQTT is a low-overhead, publicly accessible, and straightforward message exchange protocol rooted in the publish–subscribe pattern and client/server model. It fits well with limited device means, restricted bandwidth, and inconsistent network conditions. The ROSBridge rule, layered on top of the WebSocket rule, serves as a connector between ROS and other communication rules or systems. It enables two-way communication, allowing ROS to connect to and share data with external systems [21].

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Regarding information transport, command-style information primarily uses JSON (JavaScript Object Notation) and XML, with JSON being the dominant format. JSON is a lightweight data format especially suited to exchanging data between web-based apps and APIs. In a similar vein, the XML layout has also been assessed for platform use. Yet, due to XML's relatively long nature, it may increase network load. As a result, in settings where unmanned devices face resource scarcity, the JSON layout receives priority. Through this method, regardless of whether the machine is an aerial drone, a quadrupedal robot, or another apparatus, they can all exchange information using an agreed data layout, enabling interoperability. Beyond that, alignment and harmonization among machines are achieved through the previously mentioned communication rules, which govern message pushing and acceptance, enabling the distribution of machine conditions and the activation of events.

The baseline security and confidentiality expectations for the Internet of Things (IoT) encompass secrecy, integrity, availability, legitimacy, and confidentiality preservation. These expectations reflect the foundation's capacity and performance in resisting attacks and security gaps [22, 23]. In information transmission, protecting data in transit from the cloud to machines is paramount, particularly when sensitive or mission-critical information is involved [24]. The functional flow of unmanned machines typically includes receiving remote commands and actuation signals from the cloud for remote operation. These commands and actuation signals traverse various transmission channels at varying speeds, and data protection can be maintained through various safeguards and methods. Heidari *et al.* [25] put forward a deep learning-powered blockchain Intrusion Detection System (IDS) solution named BIIR. They built a secure D2X, along with a D2D interaction scheme and a blockchain-based architecture for the secure transport of protected information. System trials showed that this solution can successfully pinpoint intrusions. Prabhu Kavin *et al.* [26] debuted an inventive key derivation method based on elliptic curve cryptography (ECC), designed to produce extremely secure keys.

Furthermore, they rolled out a new binary-grounded two-phase ciphering and deciphering procedure that references key parameters from elliptic curve ciphering to provide robust protection of user information in the cloud. In this paper, we used TLS/SSL for encryption. TLS/SSL blends public-key cryptography with symmetric-key cryptography to provide end-to-end information encryption. In addition, it delivers an identity confirmation mechanism to check the legitimacy of the cloud as well as the machines. This provides strong defense for information moving from the cloud toward the machine, upholding information safety and confidentiality.

Cloud stratum

The cloud stratum primarily covers distributed processing, cloud storage, cloud functional modules, and interface engineering. The immense computational and storage capabilities afforded by the cloud foundation can be directed toward simultaneously crunching voluminous data from complex spatial settings and storing information flows packed with environmental, positional, and assignment details gathered by numerous sensors. Regarding information storage, routine positional, attributive, and instructional information is retained using the low-overhead, high-performance, non-relational cross-platform database MongoDB. Spatial scene information, conversely, is retained via the relational database PostgreSQL [27, 28]. Disparate categories of data are housed in separate databases, an approach that markedly speeds data retrieval during mass information scrutiny. The cloud stratum provides the operational modules required for various assignments, facilitating data manipulation, visual rendering, and the dispatching of applicable mission commands. Moving a heavy volume of information-crunching activities to the cloud stratum can substantially reduce the processing strain on the device stratum, thereby increasing the pace of mission completion. Interface engineering defines the data transport layout, signal semantics, and interaction patterns, adhering to guidelines such as uniformity, safety, and flexibility. This strengthens the system's trustworthiness and growth potential while shrinking production and servicing expenses.

Software Architecture

IMUC leverages a range of technological tools to assemble diverse modules and bring features to life. As shown in **Figure 2**, for the front-facing side, we use JavaScript, HTML, and CSS as the underlying technologies and incorporate

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Vue.js as the front-end framework to deliver lively user interfaces. In addition, we use ElementUI as a UI toolkit to deliver visually polished, easy-to-use interface components. On the serving side, we select Node.js as the back-end technology stack and use the Express framework to build back-end applications. This gives us the capability to efficiently field incoming client calls, communicate with databases, and use other utilities. To support information retention and handling, we use both the NoSQL store MongoDB and the relational store PostgreSQL to meet the needs of different data types. For charting operations, we use Leaflet as the mapping toolkit and integrate it with TianDiTu and Cesium to enable map viewing and interactive operations on the platform.

On top of that, we use the Potree library for spatial point cloud rendering, opening the door to visual display and scrutiny of point cloud datasets. Ultimately, to hit live information transport and dialogue, we put in place an information movement strategy anchored in WebSocket technology. This tactic guarantees real-time data flow and two-way dialogue between the client and the server, sharpening the platform's response speed and live performance.

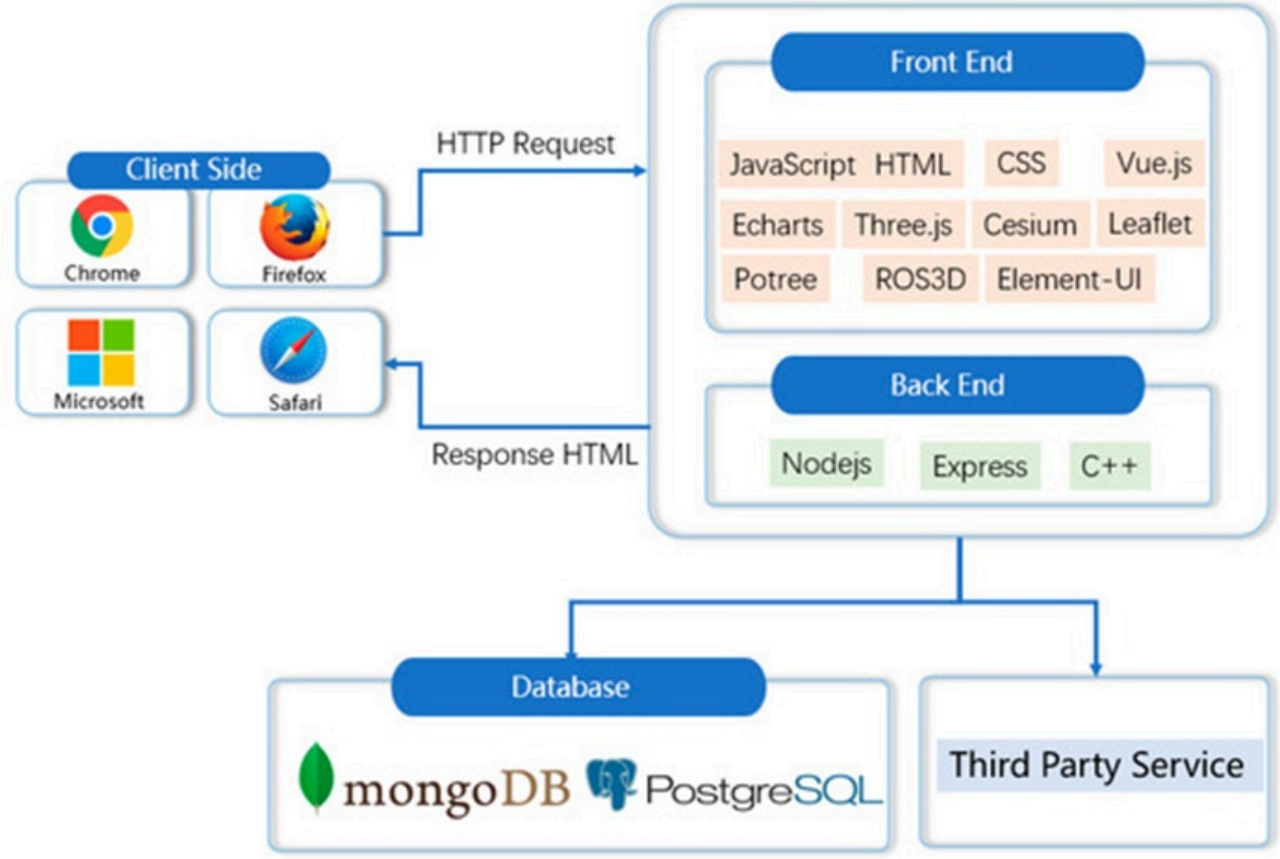

Figure 2. Software architecture.

Related Work

We set forth our associated efforts within this portion. As seen in **Figure 3**, we break the principal subject matter of IMUC into five segments for description and shall expand in depth on the technical specifics entailed.

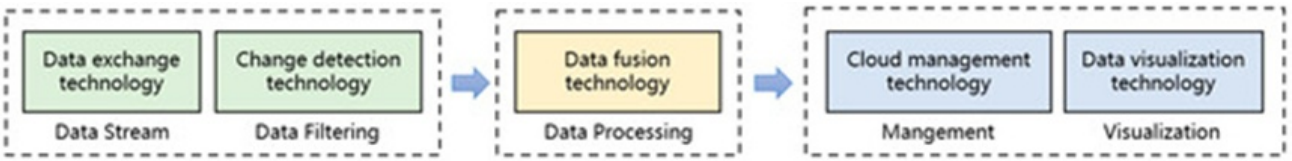

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Figure 3. Related work.

Information interchange among edge, device, and cloud foundations

Information interchange, acting as a foundational pillar of the platform's technology, serves an essential function. By applying effective information exchange techniques, it ensures the live transport of data between edge devices and cloud platforms. This means that data obtained by the edge apparatus can be promptly and precisely transmitted to cloud servers, enabling the cloud to access the freshest data for live tracking, evaluation, and decision-making. The foundation brings together various hardware components and software elements, and information interchange technology enables cross-environment teamwork, enabling disparate devices and setups to interconnect and share data effortlessly. This teamwork advances through interoperability among constituent parts, boosting the foundation's agility and growth potential. The foremost facets of foundation information interchange are explained in the following:

Camera-sourced data

The high-definition images captured by the imager mounted on the unmanned machine are transmitted to the foundation via the MQTT protocol. To start, the edge apparatus encodes the unprocessed images collected. After that, the apparatus connects to the MQTT broker and leverages its high-concurrency live streaming capabilities to deliver the encoded stream to the foundation. The foundation independently unpacks the data and uploads the images in JPG format to the server.

Lidar-sourced data

To deliver live point-cloud data from unmanned machines, the ROSBridge communication protocol is used, and point reduction is performed before transmission to reduce storage and transmission overhead. The front-facing side uses relayed data via ROSLIB and relies on Three.js for visual construction. Three.js is an open-source JavaScript library for creating and rendering dynamic spatial visual environments and motion graphics within web pages. Three.js comes with a selection of drawing pathways, allowing spatial environments to be rendered to the HTML5 Canvas, WebGL, or SVG, and supporting fast drawing of large spatial point datasets. The point-cloud information handling outlined above operates on streaming data and exhibits low lag and high reliability. Additionally, to enable thorough data exploration and pattern discovery, the foundation also rolls out a live, incremental presentation of point-cloud data, with the increment's upper bound adjustable by users. At present, open-access packages such as ROS3D do not yet support incremental display of point-cloud information within the internet client.

Video data

To handle video stream transport, Mjpg_Server is deployed at the edge tier to expose video streaming endpoints, with the ROSBridge protocol facilitating the actual data movement. This arrangement enables the smooth relay of live footage captured by imagers onboard unmanned platforms straight to the cloud infrastructure, supporting both distant surveillance and archival retention. Beyond that, each video frame is overlaid with object identification inferences that can flag pedestrians in the footage. Consequently, operators can pull up live video via this infrastructure and reliably identify and track pedestrians moving through the scene. The detection backbone selected for this purpose is YOLOv4 (You Only Look Once version 4) [29], a state-of-the-art identification pipeline that has registered notable leaps in both correctness and inference throughput. The high-level schematic of this object identifier appears in **Figure 4**. In the final step, the infrastructure is built to render the incoming video stream in the browser-based front end, allowing operators to observe and supervise the video feed live through a web panel. In brief, operators access the infrastructure via a web browser to retrieve both video feeds and object identification outputs from the unmanned platform's imager.

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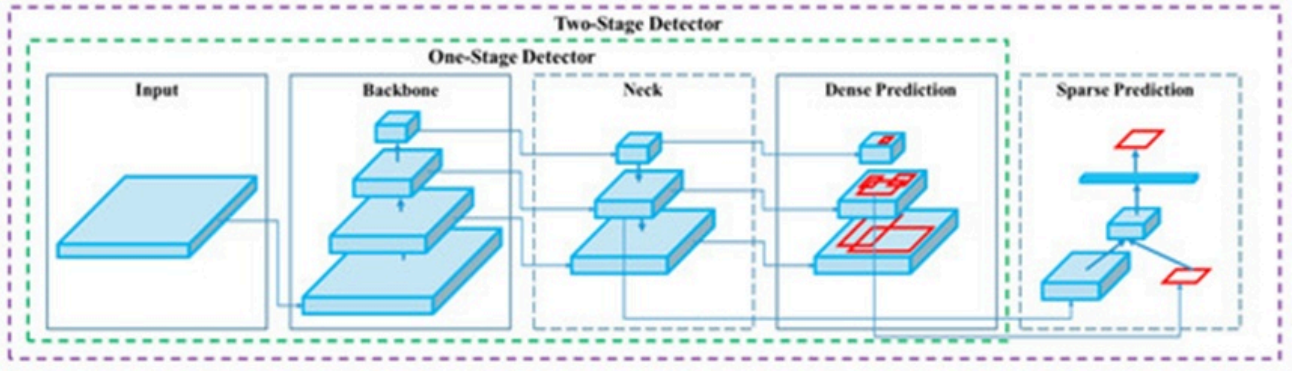

Figure 4. YOLOV4 object detector.

Location data

The infrastructure enables the live forwarding of GPS module positions from unmanned platforms to the cloud. The positional payload mainly carries longitudinal, latitudinal, and altitudinal values. While an unmanned platform operates with a GPS module throughout a sortie, the module periodically samples the platform's position, recording its current longitudinal, latitudinal, and altitudinal measurements. Through the established link with the unmanned platform, the infrastructure can push these positional fixes to the cloud in real time.

Command data

While executing defined assignments, the infrastructure routes the human supervisor's decision signals to the edge node or directly to the platform via the ROSBridge protocol. These signals span locomotion directives, activation/deactivation orders, telemetry return requests, and beyond. Via these commands, the human supervisor retains authority over the unmanned platform's movement and path guidance.

Active perception based on change detection in complex scenes

To overcome the drawbacks of low throughput, redundancy, arbitrariness, and sluggish responsiveness plaguing data-gathering workflows in complex environments, as visualized in **Figure 5**, we introduced the Global Remote Sensing Real-time Monitoring and Point-to-Point Update Cloud Platform [30]. This external infrastructure can detect persistent changes unfolding across the mission zone and forward the geolocation of altered patches to our own infrastructure. This capability lets our infrastructure immediately respond to live operational needs and take suitable steps mid-execution to hit the targets outlined below:

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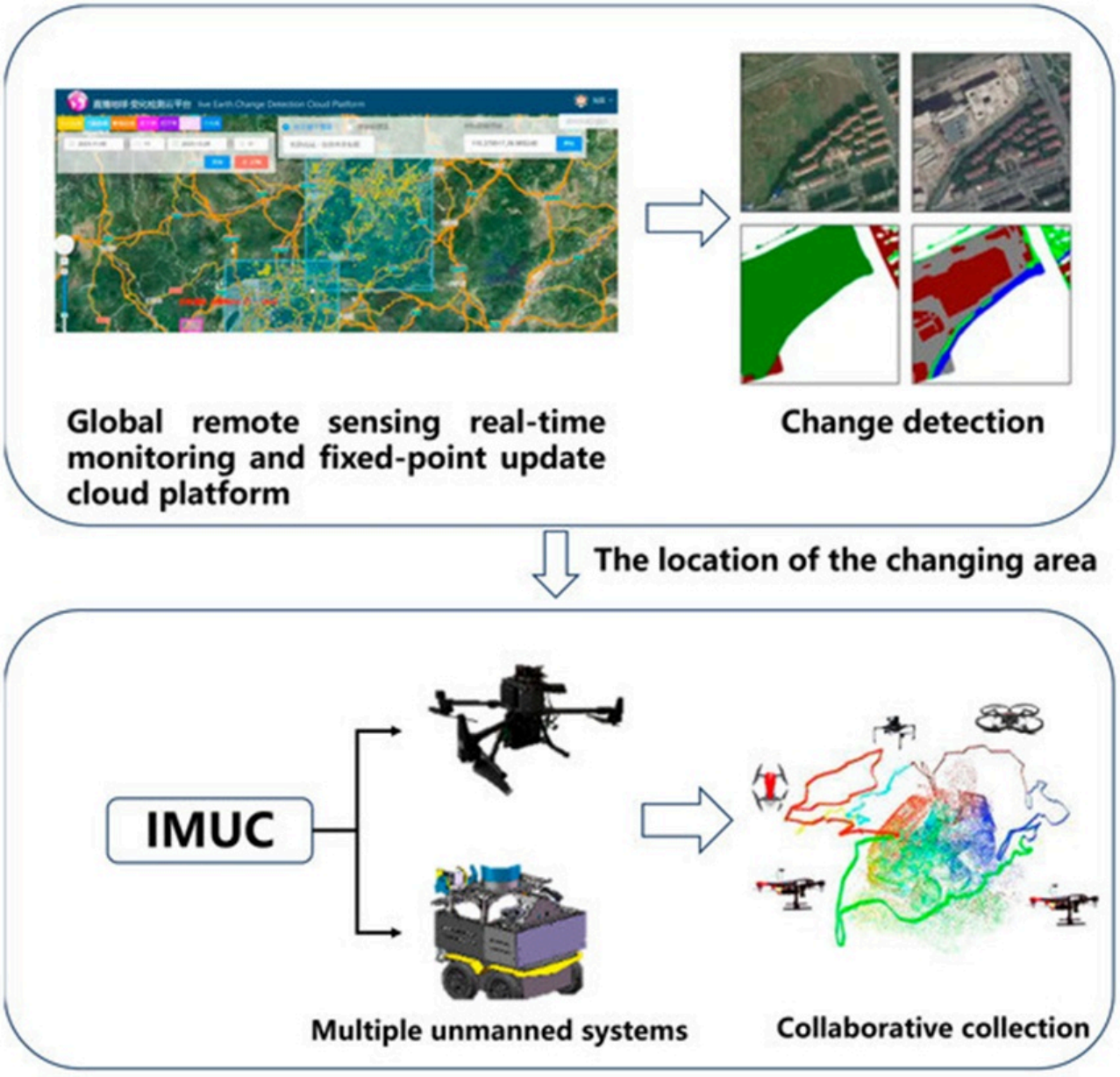

Figure 5. Data collection process based on change detection.

· Throughput enhancement: By leveraging the Global Remote Sensing Real-time Monitoring and Point-to-Point Update Cloud Platform's identification capabilities, we can swiftly gain awareness of changes within the mission zone. This does away with the necessity for wide-ranging scouting or untargeted specimen collection, trimming both time and resource burn;

· Mission fine-tuning: By securing live geolocation of the altered patches, we can perform pinpoint data collection and crunching focused on those precise zones. This lets us more faithfully record the modifications within the mission zone, thereby raising the caliber and impact of the data gathering effort;

· Prompt reaction: Thanks to the round-the-clock alteration surveillance maintained by the Global Remote Sensing Real-time Monitoring and Point-to-Point Update Cloud Platform, our infrastructure picks up these modification alerts the

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moment they arise and reacts quickly. This means we can reshape the mission execution approach dynamically to keep pace with shifting operational imperatives.

Rapid online fusion processing of multi-sensor data

Image online stitching

For the browser-based picture blending segment, we adopted the OpenREALM [31] picture blending pipeline. The flow through this pipeline is depicted in **Figure 6**, and it breaks down into five primary stages: Pose Estimation, Densification, Surface Generation, Ortho Rectification, and Mosaicing.

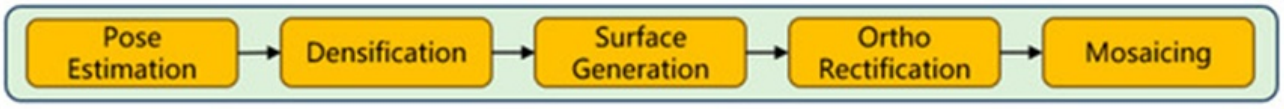

Figure 6. OpenREALM image stitching process.

First, in the Pose Estimation stage, ORBSLAM2 [32] is used to compute the imager's pose transform. Once tracking holds are provided, the frames undergo georeferenced treatment. Inbound frames may sit in a holding pattern until the computed deviation slips under a pre-set bar before they get cleared for release. During the Densification stage, the fitness of inbound frames is assessed, and, based on the pose estimate, the depth field seed is generated. After that, the frames enter the densifier boundary, where the PSL reconstruction pipeline operates. Once dense reconstruction concludes, the depth field is projected into a spatial point set, overwriting any earlier existing thin point set. The Surface Generation stage relies on the freely available toolkit "Grid Map" developed by Fankhauser and Hutter [33]. It gets bounded through regions of concern alongside the Ground Sampling Distance (GSD). Several information tiers can overlap, with each grid element built from a multi-attribute data tuple. OpenREALM additionally re-engineers select modules to cope with the performance bottlenecks inherent in dynamically inflating maps under Grid Map. Throughout the Ortho Rectification stage, a "grid-anchored ortho-mosaicking" approach is picked. It ties every picture element to a corresponding grid element and relies on interpolation and other methods to infer the quantities per element. The Mosaicing stage serves as the terminal processing point, where all previously accumulated information fuses into a single scenic depiction. Here, the full sequence of densely rebuilt and corrected frames assembles into a rich-detail mosaic.

Within our infrastructure, we grapple with the need to deliver browser-based, real-time image blending from multiple unmanned platforms, which entails ingesting feeds from numerous sensing devices. To meet this challenge head-on, as shown in **Figure 7**, we aim to tailor the OpenREALM pipeline and inject a multi-threaded execution model to permit concurrent crunching of feeds from multiple sensing devices. Through this route, we can juggle feeds from several sensing devices in parallel and eventually unify the blended outputs into one cohesive scene. This will elevate both the throughput and the live agility of our infrastructure.

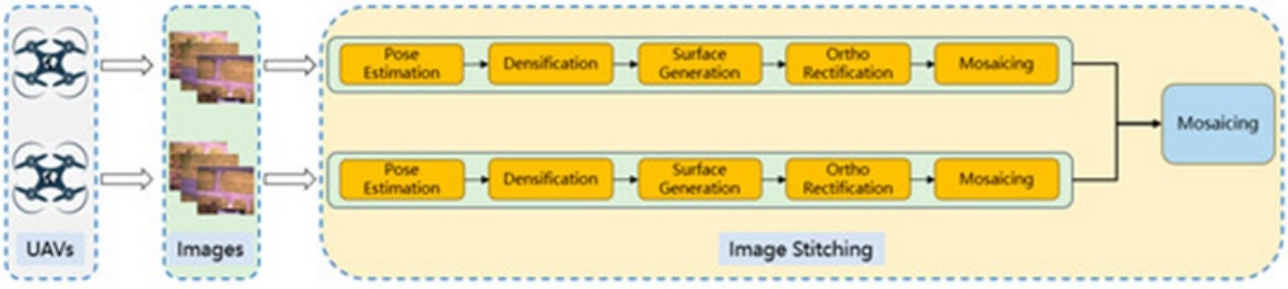

Figure 7. Online stitching of multi-sensor images.

Multi-source laser data fusion

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Throughout the data-gathering cycle, we fielded several laser-based sensors operating in concert, with each potentially contributing sweep returns from distinct observation angles or footprint extents. To yield high-grade, coherent returns, we preprocessed the harvested laser sweeps at the edge node, including steps such as noise suppression, signal conditioning, and bias correction. Following that, we registered the outputs from separate sensors into a unified coordinate framework to align them with a common spatial reference. To nullify offsets in placement and attitude, we put the point-set registration routines to work, matching and aligning point sets from separate sensors. At the end, we merged the aligned point sets to blend the returns from separate sensors into a single consolidated point set [34]. This step empowers us to display the entire point set inside the browser-based panel. Through this chain of operations, we stand to gain fuller, sharper environmental intelligence, setting the stage for downstream analysis and use.

Cloud-based unmanned system payload management and monitoring

Multi-unmanned system payload management

· Device stewardship: The infrastructure supports attachment of a broad range of device classes, including aerial rotorcraft, ground rovers, and legged robotic chassis. We must supply the device designation, network locator, and core records, including the sortie label and crew members assigned to each machine. The core records we submit are programmatically persisted into the server-side datastore and replicated onto the device information dashboard. Through this device stewardship scheme, we can systematically log and manage vital data across multiple machines. This covers device designations, letting us confidently pinpoint and distinguish different machine classes; network locators, enabling precise device discovery within the networked environment; and sortie labels and crew member records, supporting the documentation and audit trail of device employment. This structured device stewardship methodology not only helps preserve the fidelity and traceability of device behavior but also provides comprehensive insight into device linkage conditions and assignment delegation. Moreover, by storing core records in a server-hosted datastore and aligning them with the device information dashboard, we can maintain real-time awareness of device conditions and characteristics, enabling operators to provide smoother device administration capabilities.

· Group command parametrization enables customization of the variables required for data movement across multiple unmanned machines before launching a sortie. This chiefly involves specifying the primary command network address, the topic channels for laser sweeps and imager feeds for each unmanned machine, palette selections for laser sweeps arriving from distinct origins, waypoint routing and target designation, toggling the remotely steered target, and caps on peak forward and rotational speeds. Once the parametrization step completes, the variables are refreshed in the server-hosted parameter store. Through group command parametrization, we can tailor the working variables of unmanned machines to satisfy the distinct demands of each sortie. By selecting distinct palette origins for laser sweeps, we achieve sharper separation and clearer visual parsing of inputs from varied data channels. The designation of waypoint routing targets enables us to guide the pathing of unmanned machines throughout operations with exact precision. The ability to toggle the remotely steered target, paired with caps on peak forward and rotational speeds, grants adaptable governance over the movement dynamics of unmanned machines. Group command parameterization plays a significant role in the joint operation of multiple unmanned machines, boosting operational throughput while reducing costs and resource allocation.

Device monitoring

· Equipment tracking: The infrastructure receives live positional updates from unmanned machinery and concurrently refreshes the trail records as it moves, overlaying them onto the pictorial map. With this facility, operators can easily view the movement history of every unmanned asset. The system also automatically assigns different trail colours, so operators can effortlessly separate and pick out route lines linked to different assets. This facility provides operators with an at-a-glance, continuously refreshed location picture, supporting more effective oversight and analysis of unmanned machinery motion. By examining the movement behaviours and pathway patterns of unmanned assets, operators build a fuller appreciation of the machinery's operational footprint. This has substantial value for undertakings such as sortie supervision, positional evaluation, and route fine-tuning.

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· Remote command of devices: While connectivity remains normal, the infrastructure can direct the locomotion of unmanned machinery from a distance using the NippleJS on-screen joystick. NippleJS is a JavaScript resource employed to build touch-driven virtual joystick surfaces. This facility permits short-term manual intervention when unmanned ground platforms cannot self-steer or face hazards. The vector-style control provided through NippleJS enables simultaneous regulation of both the turning speed and the forward drive speed of the machinery's movement.

· Device waypoint routing control: The waypoint routing facility allows the operator to drop navigational markers on the map surface freely. It also reads the steering target specified in the group command configuration and relays the placed markers to the designated unmanned assets. Upon accepting the directives, the assets independently probe and navigate toward the designated markers. Throughout this procedure, the assets capture live environmental readings from their vicinity and feed them back to the infrastructure. This facility enables the orchestration of unmanned assets remotely for productive data harvesting. Operators can call on this function to adaptively position navigational markers for the assets, satisfying the bespoke demands of the sorties. The assets self-steer along the pre-established sequence of markers, picking up critical environmental intelligence. This distant orchestration style not only increases data-harvesting efficiency but also reduces the complexity and risk associated with hands-on steering.

Cloud route planning and massive data visualization

Cloud route planning

Worldwide path computation provides the foundation for multi-unmanned-system undertakings and serves as the decision-support layer for conducting sorties with unmanned systems. Within our infrastructure, the path computation module weighs two inputs—zone geometry and machinery count—to determine the worldwide trajectories. The infrastructure automatically forwards the path outputs as sortie directives to the unmanned machinery, and the machinery independently carries out the allocated sorties within the designated time block. As shown in **Figure 8**, the infrastructure programmatically derives worldwide trajectories based on the operator-defined mission zone and the number of unmanned assets. These worldwide trajectories function as seed paths, and should the machinery encounter blockages mid-harvest, it relies on its inbuilt collision-escaping faculties.

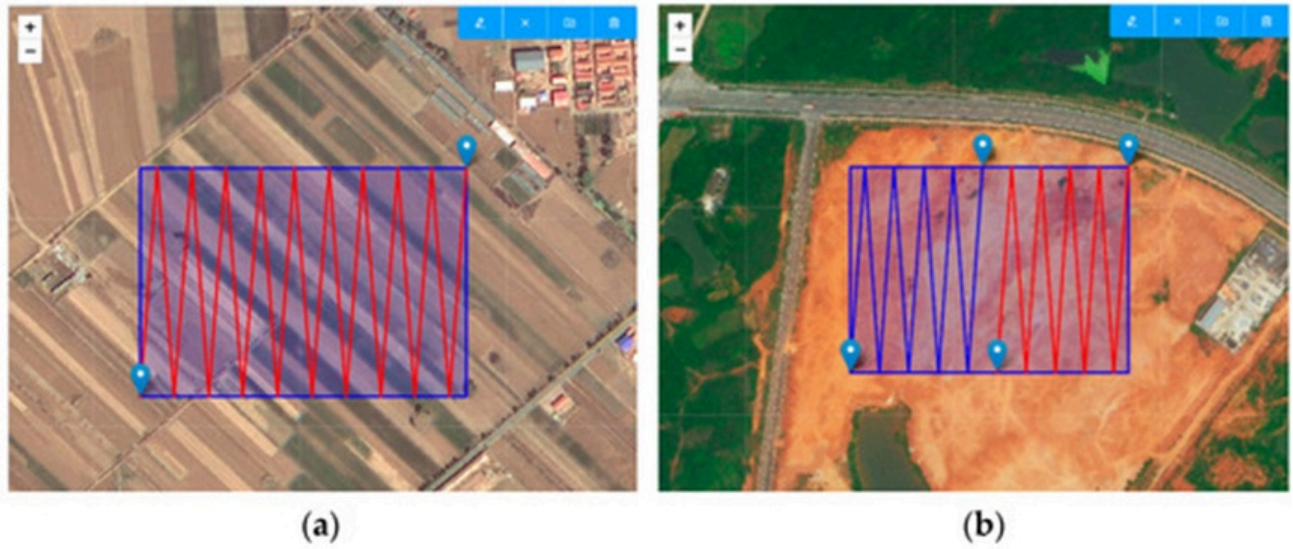

Figure 8. Global route planning. (a) Global route planning under a single unmanned device; (b) Global route planning under multiple unmanned devices.

The pseudocode of the global route planning algorithm is as follows: **Algorithm 1**.

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```
// Step 1: Set a task area
taskArea = defineTaskArea()
// Define the task area
// Step 2: Set unmanned device types and quantities
deviceList = []
For each device type and quantity:
device = createUnmannedDevice (deviceType, quantity)
// Create an unmanned device object
deviceList.push (device)
// Step 3: Plan global routes for each unmanned device based on the drawn task area
For each device in deviceList:
globalRoute = planGlobalRoute (taskArea, device)
// Plan a global route for the device
device.setGlobalRoute (globalRoute)
// Step 4: Send the global routes to each unmanned device
For each device in deviceList:
sendGlobalRouteToDevice (device, device.globalRoute)
```

Algorithm 1. Global Route Planning Algorithm

Mass data visualization

When performing measurement and mapping sorties involving several unmanned systems, amassing large batches of environmental point-set readings spanning separate flight runs is routine. However, this introduces significant obstacles when presenting datasets of this scale in a web browser. To begin with, environmental point set readings can balloon to extreme volumes, containing millions, if not billions, of discrete sample points. Shifting and fetching data at such scales runs up against ceilings set by network pipe width and storage capacity. Standard navigation technologies may hit processing chokepoints when grappling with data volumes of this magnitude, manifesting as sluggish fetch speeds or an outright inability to pull in and render the data correctly. Beyond that, manipulating and visually rendering point-set readings consume significant computational resources. Navigators usually run on endpoint devices such as desktop boxes, tablets, or pocket handsets, whose computational capacity is modest. Accordingly, performing live manipulation and drawing of point-set readings within a navigator risks triggering slowdowns, frame stutter, or application collapse. To overcome these hurdles, the infrastructure adopts the Potree [35] point-set rendering pipeline. Potree equips users with a varied toolkit for point set manipulation, scrutiny, and visual rendering, enabling operators to intuitively perceive the spread, form, and traits inherent in the data. It deploys a collection of efficiency measures, including tiered persistence and incremental fetching of point-set readings, to improve data movement and pull-in rates. By carving point set readings into several resolution tiers and adaptively pulling in data guided by the operator's vantage and requirements, Potree delivers rapid point set visualisation while easing strain on network transfers and hardware computation.

For navigator-side visual display of enormous point set readings, we rolled out the workflow described next: To start, we sent the LAS-structured point set readings to a cloud-resident server via a POST request. Following that, the server-side process running on the cloud server embeds the PotreeConverter, a point-set reformatting engine packaged with Potree. It programmatically re-expresses the LAS-structured point-set readings in the form required by Potree. As the final step, we relied on Potree for visual rendering and drawing of the enormous point-set readings. Potree employs a modified nested octree (MNO) layout, as shown in **Figure 9**, to partition point set readings into spherically bounded clusters, dramatically accelerating data browsing. To deliver an enriched point-set drawing experience, the infrastructure has

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generated several drawing styles based on intensity channels, elevation channels, RGB bands, GPS time tags, class designations, and level of detail (LOD), as shown in **Figure 10**. These drawing styles empower operators to present point-set readings in manifold ways, tailored to their personal preferences and task needs.

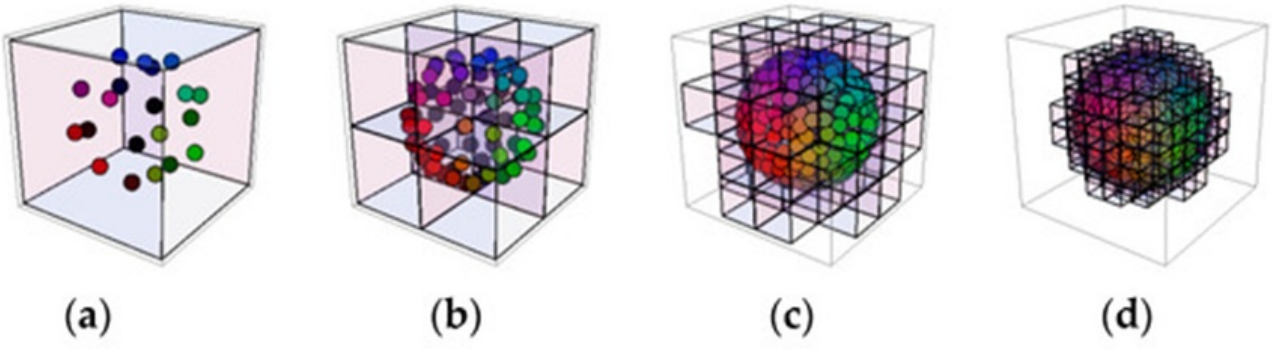

Figure 9. Spherical point cloud divided into MNO: (a) Level 0, (b) Level 1, (c) Level 2, and (d) Level 3.

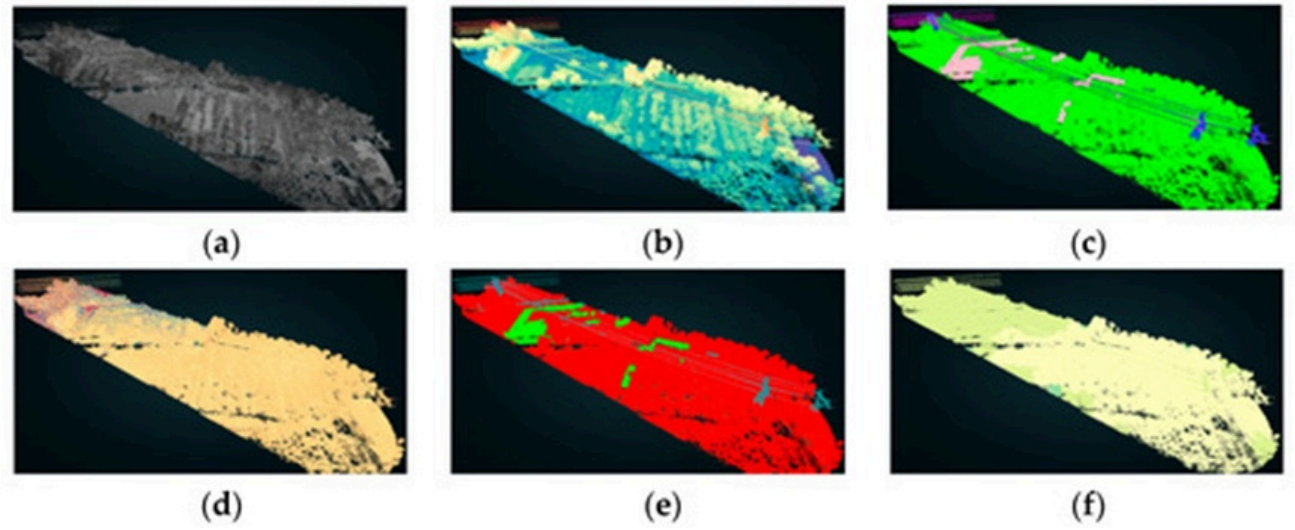

Figure 10. Transmission line point cloud rendering: (a) intensity coloring, (b) elevation coloring, (c) RGB coloring, (d) GPS time coloring, (e) classification coloring, and (f) LOD level coloring.

On top of that, the infrastructure has also implemented point-set drawing features built on the open-source spatial globe framework Cesium, which provides another visualisation avenue for point-set readings. Cesium ion, with cloud-based rendering, serves as a platform offering pre-partitioned tilesets and spatially georeferenced content. We can push data into CesiumJS-powered applications, thereby reducing the infrastructure's burden of warehousing expansive point-set readings. **Figure 11** shows the display result when fetching point-set readings stored in Cesium Ion.

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Figure 11. Display point cloud data on Cesium.

As a concluding element, we also incorporated point-set topological measure instruments into the infrastructure. The instrument set principally encompasses span, region, and angle mensuration. The mensuration instruments exploit GPU point-grasping strategies to programmatically capture the currently hovered-over point or its proximate neighbouring points for extracting coordinate readings. This approach yields rapid yet precise mensuration results. The mensuration modalities are depicted in **Figure 12**, illustrating span, angle, and region mensuration, respectively.

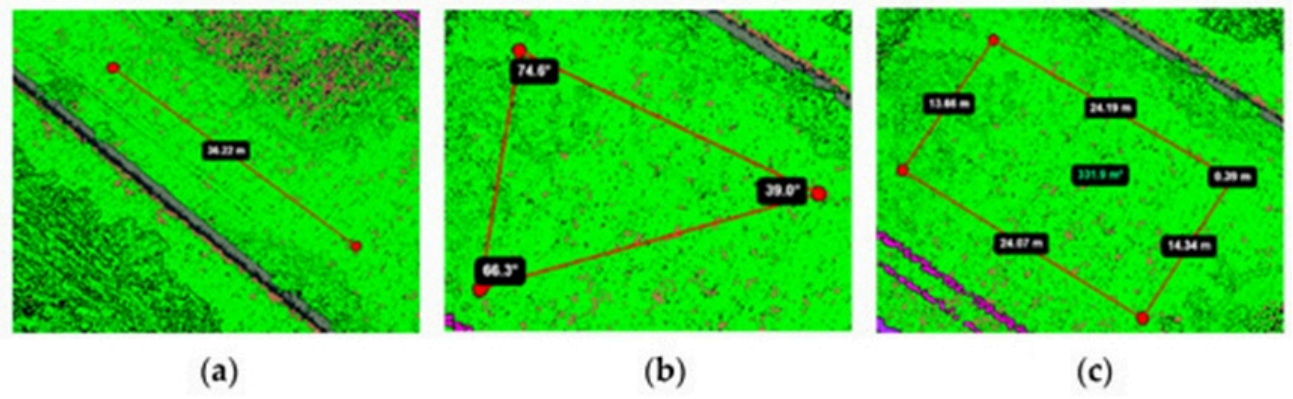

Figure 12. Point cloud measurement tools: (a) distance measurement, (b) angle measurement, and (c) area measurement.

Experiment and Comparison

Hardware platform

The equipment roster for this trial includes a pair of unmanned ground platforms (UGVs) and a single unmanned aerial platform (UAV). As represented in **Figure 13**, the UGVs rest on the BUNKER base, which utilises a track-laying differential drive train capable of performing differential pivoting. The LIDAR unit fielded is the XT32 spatial scanner, boasting a peak sensing reach of 120 m. The UGVs are outfitted with an Intel NUC11 compute module, a single-aperture

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imager, and an i300 IMU. The UAV brought into service is the Prometheus450, manufactured by AMOVLAB, as portrayed in **Figure 14**. In addition, we draw on MESH network linkages to expand the range and throughput of data movement, safeguarding efficient information flow during sortie execution. Among the sensing payloads carried by unmanned machinery, GNSS (Global Navigation Satellite System) is predominantly used to acquire geospatial fixes, which establish spatial coordinates within the geographic frame. LIDAR (Light Detection and Ranging) is an arrangement that projects laser pulses to detect targets and measure the distance to reflective surfaces. Laser rangefinding modules exhibit remarkably precise distance measurement, with fidelity down to the centimetre level. An IMU (Inertial Measurement Unit) is an inertial sensing package assembled from components such as accelerometer and magnetometer triads, and gyroscopic sensors. It forms a self-reliant navigation package that requires neither an external datum nor external signal sources, and remains immune to atmospheric influences and external perturbations. IMU serves to register object acceleration alongside rotational velocity. The imager is primarily designed to capture picture-like records of the proximate environment.

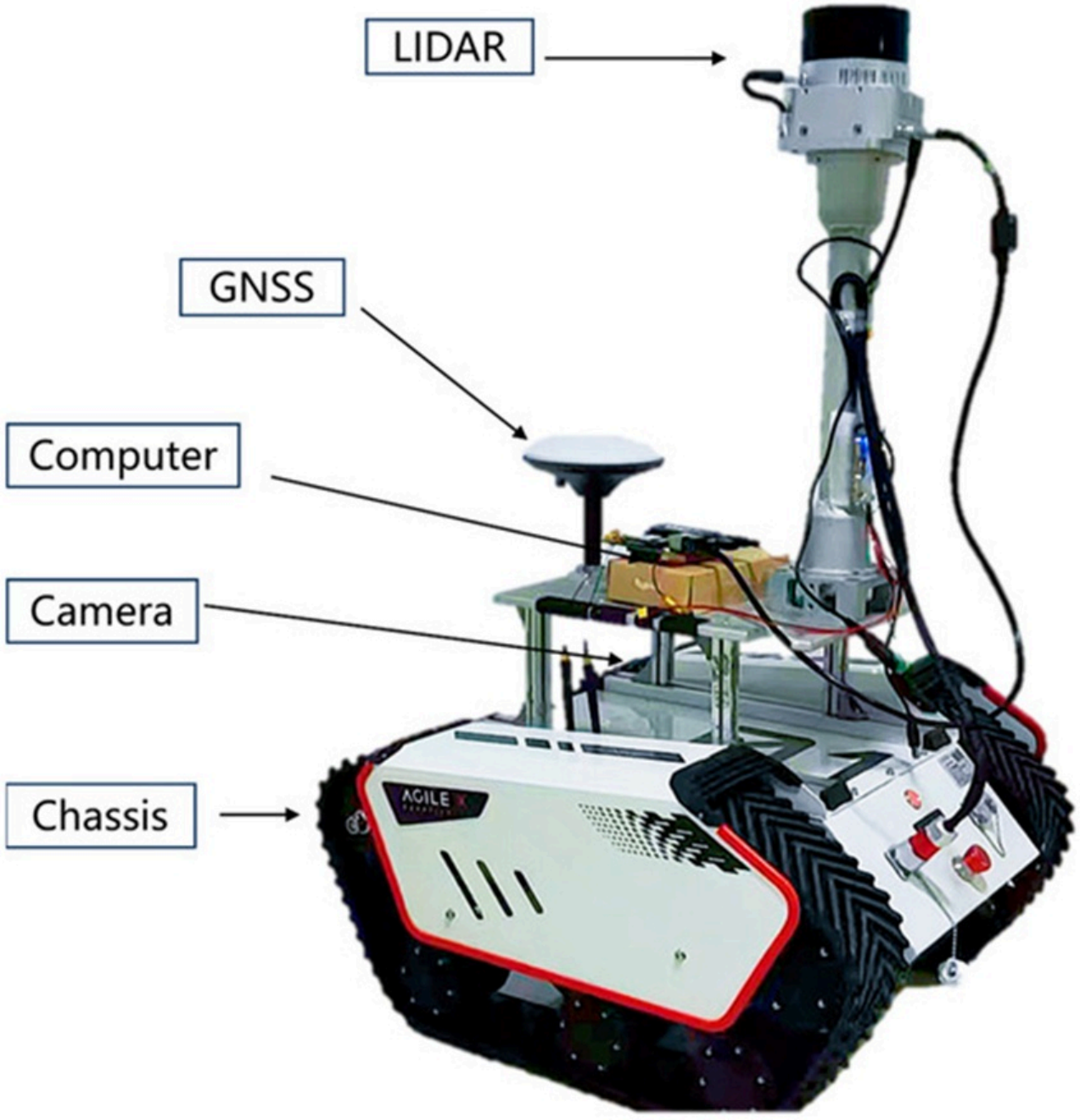

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Figure 13. Hardware composition of an unmanned ground vehicle.

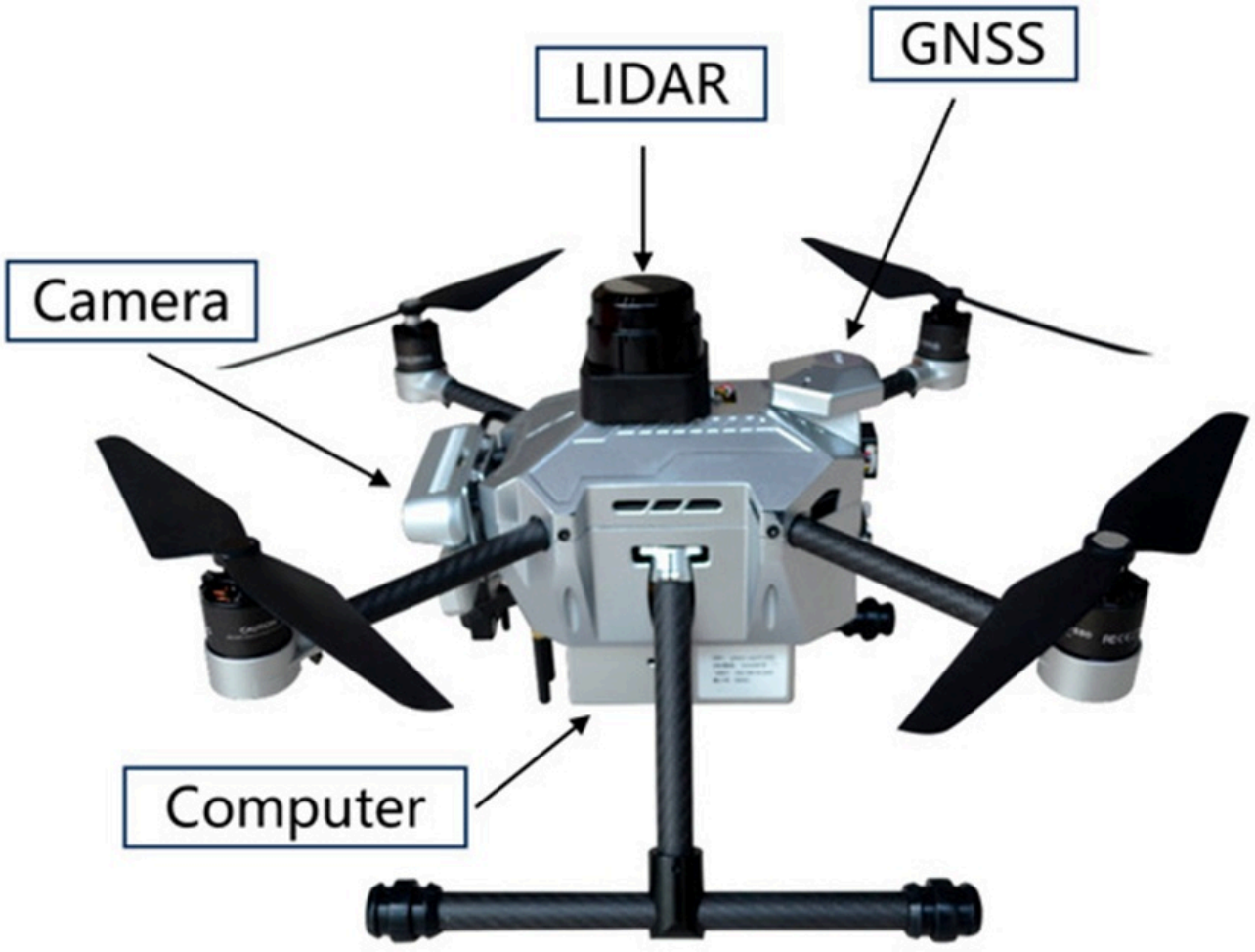

Figure 14. Hardware composition of an unmanned aerial vehicle.

Lab environment

The location chosen for this trial is within the environs of a laboratory building at Wuhan University. This locale presents an elaborate environment that furnishes ample conditions for experimental work. The landform here is varied, encompassing multiple features such as obstructions, bends, graded slopes, and towering structures. These aspects were given significant consideration when selecting the trial site. The existence of mixed obstructions allows us to replicate the behaviour of unmanned machinery in complex environments and test their collision-avoidance capabilities during sortie planning. The presence of bends and graded slopes allows us to examine the stability of unmanned machinery, including the precision of guidance across diverse terrain profiles. Beyond this, the encircling, towering structures provide an optimal testbed for probing the data movement capacity and signal consistency of the infrastructure and unmanned machinery within densely constructed zones. These complex environmental conditions introduce a degree of difficulty in conducting multi-unmanned system data-harvesting operations on the infrastructure.

Experiment procedure

The core operational flow of the trial is given in **Figure 15**. Initially, the operator positions the unmanned machinery at pre-assigned locations. The trial participant connects to the infrastructure web panel via a navigator to perform foundational operations, such as registering machinery and adjusting group command configurations. Subsequently, the trial

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participant sketches the mission zone and pushes the sortie specifics to the unmanned machinery. The machinery autonomously probes the mission zone, following the computed navigational markers. Ultimately, the harvested environmental observations are relayed back to the infrastructure and rendered on the web panel.

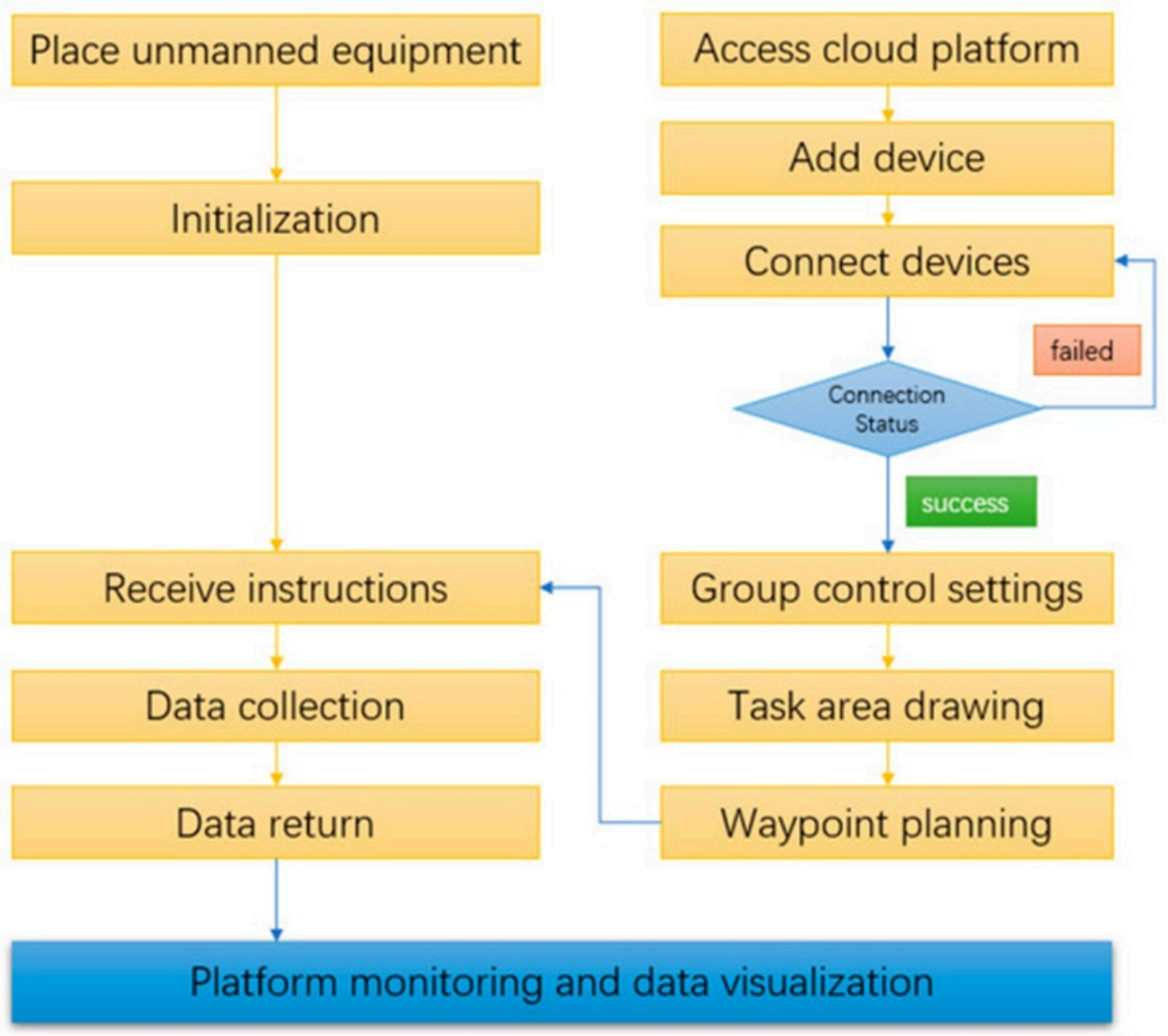

Figure 15. Experimental flow chart.

Figure 16 illustrates the computed navigational marker dataset on the infrastructure, where the unmanned ground platform self-navigates toward those coordinates. The blue dots indicate the unmanned ground platform's instantaneous location, the red dots mark the target navigational markers, and the red strokes map the ground already covered. We similarly staged test runs for scenarios involving a pair of unmanned ground platforms, as presented in **Figure 17**. The map uses distinct hues to distinguish the trails of each unmanned ground platform. On the right-hand portion, the live stacked LiDAR returns are presented. The red point set returns correspond to the readings harvested by unmanned platform 1, while the blue point set returns correspond to the readings harvested by unmanned platform 2. At this stage, point sets from separate sources are transformed into a single, unified coordinate system, enabling stacked point clouds from multiple platforms to be viewed together in a single scene. **Figure 18** renders the pathways of the two unmanned ground platforms throughout their operational period. The infrastructure logs their movement pathways and depicts them

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visually. From the pathway plot, one can observe that both unmanned ground platforms continuously push their positional updates upward, and their pathways exhibit strong loop closure, sweeping over the full set of targets within the trial zone.



Figure 16. Waypoint planning.

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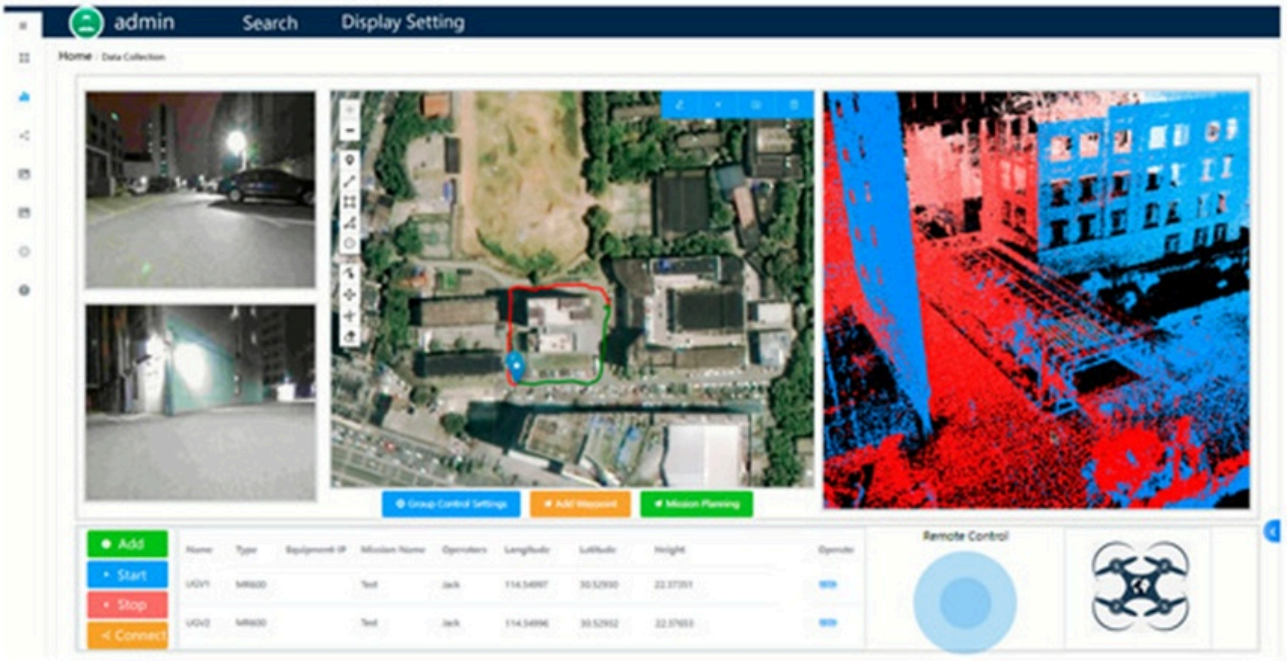

Figure 17. Multi-unmanned vehicle operation.

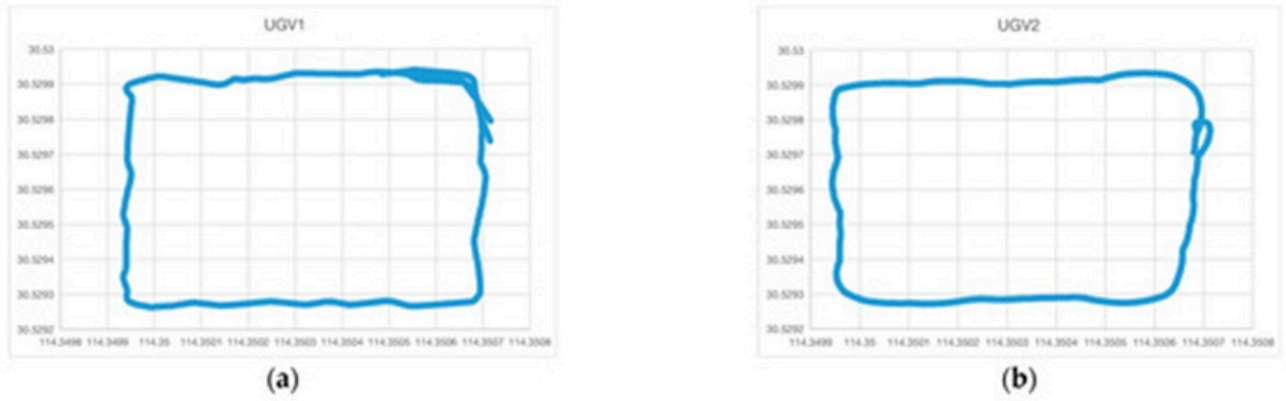

Figure 18. Trajectory diagram during unmanned vehicle testing: (a) UGV1 trajectory map, and (b) UGV2 trajectory map.

Along similar lines, we staged test runs by tethering the aerial drone to the infrastructure, as shown in **Figure 19**. The infrastructure faithfully receives GNSS readings from the drone and updates its map location without perceptible delay. Throughout the flight, the tether between the infrastructure and the drone remains solid, ensuring the reliability of smart decision-making on the infrastructure side.

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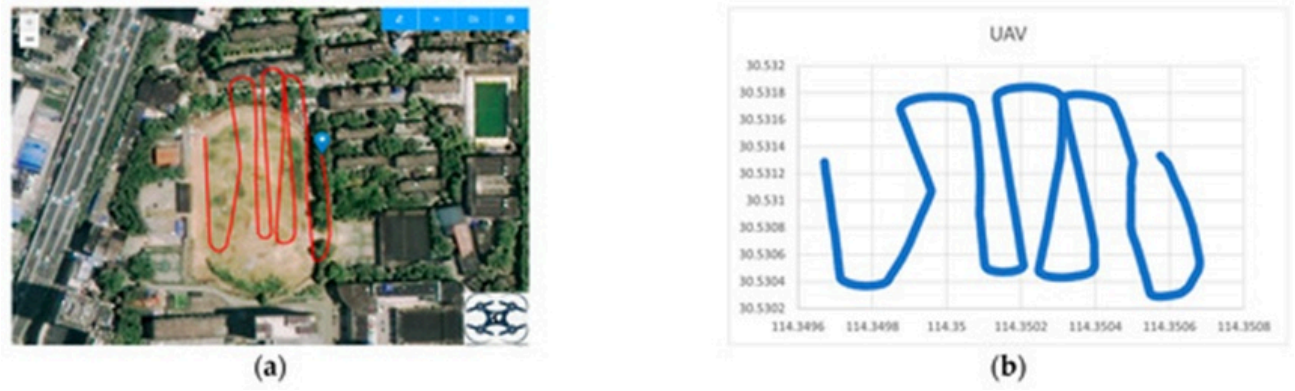

Figure 19. Drone operations: (a) real-time position feedback during drone operations, and (b) drone trajectory map.

Experimental results and analysis

The complete experimental campaign spanned 10 field deployments. Within these, the infrastructure was evaluated alongside several unmanned ground platforms across five deployments, culminating in an aggregate data harvest of roughly 2782.8855 MB. This corpus comprises 1601.23 MB of LiDAR captures, 1181.34 MB of camera captures, and 0.3155 MB of GNSS captures. The itemised figures are presented in **Table 1**. The infrastructure likewise underwent evaluation alongside the aerial drone across five deployments, yielding an aggregate data harvest of roughly 381.0309 MB. This corpus comprises 380.856 MB of camera captures and 0.1749 MB of GNSS captures. The itemised figures are presented in **Table 2**.

Table 1. Multi-autonomous vehicle test results.

Trial No.	Recording date	Session length	GNSS log size (MB)	Vision sensor data (MB)	LiDAR dataset size (MB)	Experimental platform
1	3 June 2023	9 min 5 s	0.0515	190.84	263.67	Unmanned Ground Vehicles (UGVs)
2	5 June 2023	10 min 19 s	0.0544	205.08	275.53	Unmanned Ground Vehicles (UGVs)
3	8 June 2023	8 min 25 s	0.0491	182.47	236.72	Unmanned Ground Vehicles (UGVs)
4	9 June 2023	15 min 12 s	0.0826	323.33	436.41	Unmanned Ground Vehicles (UGVs)
5	12 June 2023	13 min 21 s	0.0779	279.62	388.90	Unmanned Ground Vehicles (UGVs)

Table 2. Drone test experimental results.

Number	Date	Experiment duration	GNSS data (MB)	Camera data (MB)	Laboratory equipment
1	2 June 2023	5 min 1 s	0.0291	64.492	UAV
2	5 June 2023	4 min 21 s	0.0266	56.124	UAV
3	7 June 2023	6 min 11 s	0.0366	81.761	UAV

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4	13 June 2023	8 min 36 s	0.0513	112.322	UAV
5	15 June 2023	5 min 2 s	0.0313	66.157	UAV

Across the entire data-harvesting window, every platform successfully accepted directives and completed the data-gathering assignments with zero information loss. The rendering of accumulated LiDAR captures proceeded smoothly, enabling ordinary interaction with point-set content within the spatial scene. Over time, the LiDAR captures were refreshed in a stepwise manner. Turning to camera imagery, the pictures were rendered without interruption, permitting unambiguous recognition of the neighbouring environment. The intake of GNSS readings proceeded as expected, and the status dashboard updated with negligible delay. No meaningful discrepancies surfaced between the positional estimates of the unmanned platforms and their true geographic locations. Throughout the operational span, the infrastructure proved capable of monitoring platform conditions while visually depicting data-harvesting outcomes. This guaranteed the high-calibre fulfilment of the experimental run and reinforced its trustworthiness and fidelity.

Platform performance testing

Stress evaluation of the infrastructure was conducted within a local-area network environment. The evaluation workstation featured an Intel Core i7-12700H@2.30 GHz processor, 16 GB of RAM, and an NVIDIA GeForce RTX 3050 graphics processor. As detailed in **Table 3**, the Locust harness was used to simulate varying numbers of unmanned platforms issuing calls to the infrastructure, thereby gauging its capacity under load. Each evaluation round lasted 1 minute. A clear pattern emerges: the mean reply delay of the infrastructure increases in step with the number of drones, while the peak reply delay generally increases. As a case in point, at a count of 20 unmanned units, the peak reply delay is 29 ms, a figure within tolerable limits.

Furthermore, no call failures were recorded across the entire 147,630 calls, underscoring the robustness of the infrastructure. **Table 4** captures the infrastructure's resource consumption profile after a sustained period of steady operation. CPU utilisation remains below 10%, memory consumption is below 1 GB, and GPU utilisation is below 55%. Scrutinising the consumption profile reveals that GPU draw is comparatively elevated, predominantly attributable to drawing routines tied to a large body of spatial content. **Table 5** presents the throughput metrics for the principal data categories traversing the infrastructure. Throughput for LiDAR captures, camera captures, and miscellaneous command traffic sits around 0.52 MB/s, 0.36 MB/s, and 0.12 MB/s, respectively. Prevailing network conditions largely determine the tempo of data movement.

Table 3. Performance testing of connecting different numbers of unmanned devices.

Number	Number of unmanned devices	Max (ms)	Min (ms)	Average (ms)	Median (ms)	Fails	Requests
1	5	14	1	2	2	0	132,437
2	10	13	2	3	3	0	162,549
3	15	18	1	5	5	0	148,449
4	20	29	3	6	7	0	147,630
5	25	41	2	8	8	0	153,998
6	30	72	4	9	9	0	167,087

Table 4. Resource usage.

CPU (%)	Memory (GB)	GPU (%)

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< 10	< 1	< 55

Table 5. Data transfer rate.

Laser data	Camera data	Other instruction data
0.52 MB/S	0.36 MB/S	0.12 MB/S

Platform comparison

At this point, we place our infrastructure alongside analogous offerings and frameworks, as catalogued in Table 6. Seven separate functional dimensions served as the yardsticks for comparison. The first dimension concerns the capacity to onboard fresh unmanned platforms into the infrastructure, with setup handled through the infrastructure itself. The second dimension concerns oversight of several unmanned units, including inspections of their current condition and geographic locations, as well as alterations to each unit's configuration. The third dimension covers live observation of GPS fixes, velocity readings, and video transmissions emanating from the unmanned platforms. The fourth dimension concerns the ability to calculate global trajectories for unmanned platforms anchored in the designated mission zone. The fifth dimension is the browser-based merging of overhead pictures harvested by unmanned platforms. The sixth dimension involves the browser-based presentation of readings from multiple sensor types, spanning LiDAR captures, camera outputs, GNSS readings, and similar. The seventh dimension is point set manipulation, unlocking cloud-hosted operations such as trimming, visual styling, and dimensional measurements applied to point set content.

Table 6. Platform comparison.

Capabilities	Pino M [14]	DroneTrack [15]	WebODM [36]	QGroundControl [37]	Foxglove [38]	IMUC
Robot setup and configuration	√	√	√	√	√	√
Support for managing multiple robots	√	√		√	√	√
Real-time robot status monitoring	√	√		√	√	√
Robot path and route planning				√		√
Live image stitching functionality	√		√			√
Visualization of multi-sensor information					√	√
Point cloud analysis and processing			√			√

Results and Discussion

Operating as a consolidated infrastructure, IMUC occupies a meaningful position in underpinning and refining the cooperative undertakings of several unmanned systems. This matter carries substantial consequences for the evolution of the surveying and mapping domain. In the discussion section of this paper, we examine in depth the technical stumbling blocks the infrastructure faces and survey potential remedies. In addition, we examine the feasibility of integrating the infrastructure with artificial intelligence and machine learning. Finally, we weigh the obstacles this

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infrastructure could encounter during real-world uptake within the surveying and mapping domain and advance feasible countermeasures.

· Technical stumbling blocks encountered: First and most critically, we devote keen attention to boosting information movement throughput under field conditions, as this parameter heavily shapes the live reactivity of the infrastructure. Within the unmanned systems sphere, maximising information throughput is a linchpin for productive, intelligent sortie execution. At this stage, the live reactivity of the infrastructure depends heavily on the quality of the network backbone. Our current countermeasure primarily entails compressing and reducing data to the greatest extent possible to reduce data transmission latency. This countermeasure nonetheless comes with built-in ceilings. As communication technology marches steadily forward, swifter and more dependable network fabrics and protocols will eventually satisfy the hunger for high-capacity information movement. Second, we encounter the challenge of sluggish navigator-side rendering of expansive spatial content. Drawing tempo can be lifted through the construction of octree index structures and the application of level-of-detail (LOD) strategies to regulate the richness of detail presented. Even so, as data volumes press relentlessly upward, ever more refined methods and computational recipes become necessary to sustain inspection tempo for enormous spatial corpora. We are actively exploring the use of cloud computing and distributed processing models to address the generation of expansive spatial content. By distributing drawing duties across a pool of processing nodes for concurrent execution, drawing tempo can be accelerated while the overall system's live responsiveness improves. Additionally, by capitalising on the elastic and stretchable nature of cloud computation assets, we can adaptively modulate the scale of processing capacity to match varying extents and intricacies of spatial geodata, precisely as circumstances demand;

· Fusing with artificial intelligence and machine learning: The fusion with artificial intelligence (AI) and machine learning (ML) disciplines carries notable weight in the realms of information movement and manipulation. Through the application of these disciplines, the intelligent distribution and orchestration of sorties becomes realisable. Drawing upon considerations such as the inherent character of sorties, their urgency, the current condition, and the inherent faculties of the robotic machinery, computational recipes can independently settle on which machines receive which sorties and arrange the sequential fulfilment of sorties to hit peak sortie completion throughput. Moreover, while undertaking live scrutiny and manipulation of raw sensor feeds, worthwhile signals or distinguishing traits can be isolated, interference or aberrant readings can be filtered out, and information compression and archival strategies can be tuned, thereby increasing information manipulation throughput and overall performance. We plan to pursue deeper investigation and embed these disciplines directly into the infrastructure to bring about more productive and intelligent operational modes;

· Uptake within the surveying and mapping domain: Through this infrastructure, the surveying and mapping domain is well-positioned to achieve more productive and accurate geographic information harvesting and manipulation, translating into measurable value and real-world impact. The infrastructure streamlines the surveying and mapping workflow by mechanising information harvesting, scrutiny, and visualisation, thereby increasing throughput and overall output. It reduces manual intervention and time-intensive tasks, conserving both time and operational resources. **Figure 20** outlines the uptake pathways for the surveying and mapping domain, along with the principal technical conduits involved. Our infrastructure sees uptake inside the surveying and mapping domain and furnishes concrete, hands-on benefits. For example, emergency relief efforts can support rescue crews by enabling remote operations and visual representation of on-the-ground conditions at the disaster site. Such a capability not only enables rapid reconstruction of field conditions but also enhances safety by reducing physical proximity to hazardous surroundings or challenging landforms. That said, embedding this infrastructure into the surveying and mapping domain could encounter several potential friction points. Firstly, there are misgivings about data trustworthiness and data safeguarding. The surveying and mapping domain imposes stringent benchmarks for data trustworthiness, encompassing high accuracy and high granularity. Suitable measures must be instituted to ensure data trustworthiness and correctness throughout the information harvesting pipeline. Beyond that, it is imperative to strengthen data protection and confidentiality to preserve the integrity of the information. Secondly, the hurdle of moving and visually rendering multi-sensor feeds within intricate survey settings persists. With the growing intricacy of the settings we encounter, a larger suite of sensors is typically fielded, which adds layers of complication to information unification and visual portrayal. This demands ongoing iterative enhancement of

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information conversion and normalisation tooling, alongside information unification approaches, to realise the blending of multi-source feeds.

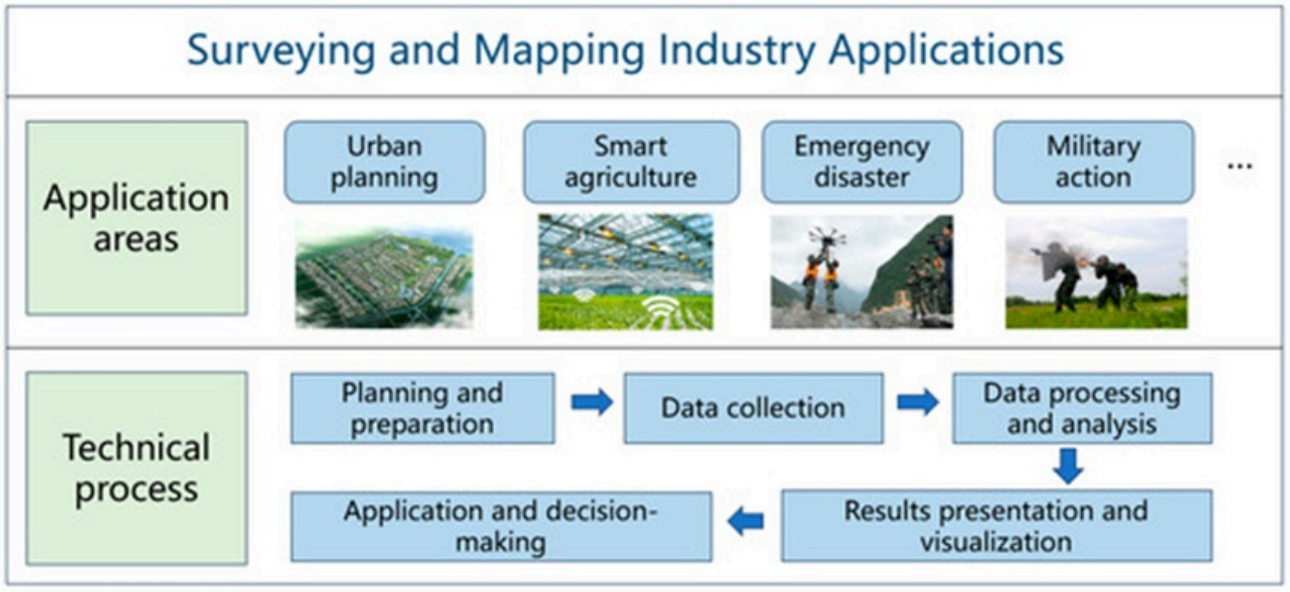

Figure 20. Surveying and mapping industry applications.

Conclusion

The objective of this paper is to improve the efficiency of cooperative information-harvesting campaigns involving multiple unmanned systems in complex environments. We rely on cloud computing and cloud storage to alleviate the processing and storage bottlenecks inherent in single-machine configurations. The infrastructure we architected and brought to life offers multiple consequential strengths, among which are the following:

· Our infrastructure implements a batch-plus-streaming hybrid information movement paradigm. This paradigm empowers us to realise the transfer and mutual exchange of dissimilar payload information originating from multiple sources, safeguarding both the timeliness of live delivery and the completeness of information delivery. Whether dealing with rigidly organised or loosely structured information, both categories can be moved and swapped productively and dependably across this infrastructure;

· By sharpening the oversight and supervision capabilities for multiple unmanned systems from a cloud vantage point, our infrastructure maintains operational safety during real-world operations. This encompasses, though is not confined to, live tracing of the geographic positions of unmanned hardware, continual observation of hardware operating conditions, and instantaneous reception of warning dispatches from alert subsystems. Moreover, the infrastructure unlocks fast browser-based merging, manipulation, and shared situational awareness from multiple sensor feeds;

· Our infrastructure delivers a broad set of capabilities through visual engineering for cloud-hosted sortie and trajectory planning. These capabilities span multi-layered toggling, adjustment, and visual computation of payload-related settings, offline stepping through archived records, and quantitative summarisation of enormous datasets. Operators can productively lay down trajectories, fine-tune payload settings, browse stored records, and conduct data-driven scrutiny through a clean, intuitive interface. This substantially lifts the ease and productivity of managing unmanned systems.

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To summarize, this paper constructed a consolidated, high-throughput processing infrastructure governed by a cloud-resident central coordination brain, augmented by edge computation and intelligent endpoint exchanges. The fruits of this endeavour are of considerable significance for improving the efficiency of cooperative information-harvesting campaigns involving multiple unmanned systems in complex settings. Forthcoming research efforts will press further into the optimisation of data visualisation and the strengthening of system-wide live reactivity. We shall take a broader set of variables into account and probe more productive sortie distribution and trajectory-computation recipes capable of contending with increasingly intricate environments and mission specifications. In parallel, we shall also consider broadening the functional repertoire of the infrastructure to serve a wider range of application sectors and operational contexts.

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Conflict of interest

None

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Ethics statement

None

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References

1. Lei GP. Research on optimization of cloud-based control system for agricultural drone in crop protection. J Agric Mech Res. 2023;45:5.

2. Cao K, Liu Y, Meng G, Sun Q. An overview on edge computing research. IEEE Access. 2020;8:85714-28.

3. Kim B, Jang J, Jung J, Han J, Heo J, Min H. A computation offloading scheme for uav-edge cloud computing environments considering energy consumption fairness. Drones. 2023;7:139.

4. Xu Y, Li L, Sun S, Wu W, Jin A, Yan Z, et al. Collaborative Exploration and Mapping with Multimodal LiDAR Sensors. In: Proceedings of the 2023 IEEE International Conference on Unmanned Systems (ICUS); Hefei, China; 2023.

5. Nohel J, Stodola P, Flasar Z, Křišťálová D, Zahradníček P, Rak L. Swarm Maneuver of Combat UGVs on the future Digital Battlefield. In: Proceedings of the International Conference on Modelling and Simulation for Autonomous Systems; Prague, Czech Republic, 2022; Springer International Publishing: Cham, Switzerland;2022. p. 209-30.

6. Zhang Y, Yu J, Tang Y, Deng Y, Tian X, Yue Y, et al. GACF: Ground-Aerial Collaborative Framework for Large-Scale Emergency Rescue Scenarios. In: Proceedings of the 2023 IEEE International Conference on Unmanned Systems (ICUS); IEEE, Hefei, China; 2023. p. 1701-7.

7. Berger GS, Teixeira M, Cantieri A, Lima J, Pereira AI, Valente A, et al. Cooperative heterogeneous robots for autonomous insects trap monitoring system in a precision agriculture scenario. Agriculture. 2023;13:239.

8. Zhao M, Li D. Collaborative task allocation of heterogeneous multi-unmanned platform based on a hybrid improved contract net algorithm. IEEE Access. 2021;9:78936-46.

9. Zhou X, Wen X, Wang Z, Gao Y, Li H, Wang Q, et al. Swarm of micro flying robots in the wild. Sci Robot. 2022;7:eabm5954.

10. Stolfi DH, Brust MR, Danoy G, Bouvry P. UAV-UGV-UMV multi-swarms for cooperative surveillance. Front Robot AI. 2021;8:616950.

11. Potena C, Khanna R, Nieto J, Siegwart R, Nardi D, Pretto A. AgriColMap: Aerial-ground collaborative 3D mapping for precision farming. IEEE Robot Autom Lett. 2019;4:1085-92.

12. Tagarakis AC, Filippou E, Kalaitzidis D, Benos L, Busato P, Bochtis D. Proposing UGV and UAV systems for 3D mapping of orchard environments. Sensors. 2022;22:1571.

13. Asadi K, Suresh AK, Ender A, Gotad S, Maniyar S, Anand S, et al. An integrated UGV-UAV system for construction site data collection. Autom Constr. 2020;112:103068.

14. Pino M, Matos-Carvalho JP, Pedro D, Campos LM, Seco JC. UAV cloud platform for precision farming. In: Proceedings of the 2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP); IEEE, Porto, Portugal; 2020. p. 1-6.

15. Koubaa A, Qureshi B. DroneTrack: Cloud-Based real-time object tracking using unmanned aerial vehicles over the internet. IEEE Access. 2018;6:13810-24.

16. DJI. Skysense Cloud Platform. https://enterprise.dji.com/flighthub-2?site=enterprise&from=nav (accessed on 29 August 2023).

17. Kitebeam Aerospace Company. Kitebeam Unmanned Platform. https://kitebeam.com (accessed on 27 August 2023).

18. Rottmann N, Studt N, Ernst F, Rueckert E. Ros-mobile: An Android application for the robot operating system. arXiv. 2020;arXiv:2011.02781.

19. Labib NS, Brust MR, Danoy G, Bouvry P. The rise of drones in internet of Things: A survey on the evolution, prospects and challenges of unmanned aerial vehicles. IEEE Access. 2021;9:115466-87.

20. Rana B, Singh Y. Internet of Things and UAV: An interoperability perspective. In: Unmanned Aerial Vehicles for Internet of Things (IoT) Concepts, Techniques, and Applications; John Wiley and Sons: Hoboken, NJ, USA; 2021. p. 105-27.

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21. Penmetcha M, Kannan SS, Min BC. Smart cloud: Scalable cloud robotic architecture for web-powered multi-robot applications. In: Proceedings of the 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC); IEEE, Toronto, ON, Canada; 2020. p. 2397-402.

22. Yahuza M, Idris MYI, Ahmedy IB, Wahab AWA, Nandy T, Noor NM, et al. Internet of drones security and privacy issues: Taxonomy and open challenges. IEEE Access. 2021;9:57243-70.

23. Wazid M, Das AK, Lee JH. Authentication protocols for the internet of drones: Taxonomy, analysis and future directions. J Ambient Intell Humaniz Comput. 2018;1-10.

24. Yang W, Wang S, Yin X, Wang X, Hu J. A review on security issues and solutions of the Internet of Drones. IEEE Open J Comput Soc. 2022;3:96-110.

25. Heidari A, Navimipour NJ, Unal M. A secure intrusion detection platform using blockchain and radial basis function neural networks for internet of drones. IEEE Internet Things J. 2023;10:8445-54.

26. Prabhu Kavin B, Ganapathy S, Kanimozhi U, Kannan A. An enhanced security framework for secured data storage and communications in cloud using ECC, access control and LDSA. Wirel Pers Commun. 2020;115:1107-35.

27. Matallah H, Belalem G, Bouamrane K. Comparative study between the MySQL relational database and the MongoDB NoSQL database. Int J Softw Sci Comput Intell IJSSCI. 2021;13:38-63.

28. Makris A, Tserpes K, Spiliopoulos G, Zissis D, Anagnostopoulos D. MongoDB Vs PostgreSQL: A comparative study on performance aspects. GeoInformatica. 2021;25:243-68.

29. Bochkovskiy A, Wang CY, Liao HYM. Yolov4: Optimal speed and accuracy of object detection. arXiv. 2020;arXiv:2004.10934.

30. Zhong R, Li Q, Zhou C, Li X, Yang C, Zhang S, et al. Design and implementation of global remote sensing real-time monitoring and fixed-point update cloud platform. Natl Remote Sens Bull. 2022;26:324-34.

31. Kern A, Bobbe M, Khedar Y, Bestmann U. OpenREALM: Real-time mapping for unmanned aerial vehicles. In: Proceedings of the 2020 International Conference on Unmanned Aircraft Systems (ICUAS); IEEE, Athens, Greece; 2020. p. 902-11.

32. Mur-Artal R, Tardós JD. Orb-slam2: An open-source slam system for monocular, stereo, and RGB-D cameras. IEEE Trans Robot. 2017;33:1255-62.

33. Fankhauser P, Hutter M. A universal grid map library: Implementation and use case for rough terrain navigation. Robot Oper Syst (ROS) Complet Ref. 2016;1:99-120.

34. Xu Y, Chen C, Wang Z, Yang B, Wu W, Li L, et al. PMLIO: Panoramic Tightly-Coupled Multi-LiDAR-nertial Odometry and Mapping. ISPRS GSW. 2023;5:703-8.

35. Schütz M. Potree: Rendering Large Point Clouds in Web Browsers; Technische Universität Wien: Wiedeń, Österreich, 2016.

36. OpenDroneMap Team. WebODM Software. https://www.opendronemap.org/webodm/ (accessed on 21 August 2023).

37. PX4 Team. QGroundControl Software. http://qgroundcontrol.com/ (accessed on 23 August 2023).

38. Foxglove Company. Foxglove Official Website. https://console.foxglove.dev/ (accessed on 20 August 2023).

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