Chapter 2
Robot Operating System Powered Data Acquisition for Unmanned Aircraft Systems in Digital Agriculture

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Abstract Unmanned aircraft systems (UAS) have been popularized recently for agricultural applications. While many commercial and open-source solutions have been and are being developed, limited efforts have been made for custom data acquisition systems which are crucial to address major technical issues in the current UAS systems for agriculture. This chapter aims to provide a conceptual framework based on robot operating system (ROS) for the design and development of custom data acquisition (DAQ) systems for UAS in agriculture. Design concepts and major implementation details are provided to facilitate future development. A case study is given in this chapter to demonstrate the use of the conceptual framework to design and implement a ROS-based data acquisition system for a commercial drone. The case study also demonstrated the success of the developed system for image acquisition in a hemp breeding experiment and the value of using UAS sensing systems for high throughput phenotyping in hemp. Therefore, the proposed conceptual framework can be used as a reference to develop custom DAQ systems in future studies.

2.1 Introduction

Agriculture is facing tremendous challenges caused by the continuously growing world population along with major environmental [13] and social issues [19] such as climate change [12], limited arable land and water resources [24], and labor shortage [39]. Past efforts have focused on addressing specific issues: the Green Revolution aimed for yield increases but not resource use efficiency; agricultural mechanization revolution aimed for productivity but not pollution and environmental consequences; and precision agriculture aimed for optimal return over investment but not equity. The new digital agriculture (DA) revolution aims to digitize the whole supply chain of agrifood systems and provides systems solutions to massive aforementioned challenges [2].

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Unmanned aircraft systems (UAS), or drones in many recent research studies, are a key DA component that offers mobility to sensing and actuation operations for agricultural applications [1, 9, 14, 18, 32, 35]. Based on the driving-mode, UAS platforms can be categorized as three groups: (1) single-rotors, (2) multirotors, and (3) fixed-wing platforms [14]. Single-rotors (e.g., helicopters) and fixed-wing platforms have been widely used in remote sensing and spraying in agriculture for a long time [35]. Due to improved operability, reduced cost, and sufficient market availability, multirotors have been recently popularized for both agricultural research and production management, especially for high throughput plant phenotyping [9, 35]. Compared with other mobile platforms (e.g., ground and satellite systems), multirotors offer a unique balance between sensing coverage and resolution. Typically, a multirotor-based system has a flight duration of 20 to 30 minutes, which can cover up to 100 acres with a sensing resolution at the millimeter to centimeter (or organ to plot) levels [29, 30, 37]. This throughput and resolution combination would be sufficient for plant- and plot-level research studies and breeding as well as decision-making support in production systems. Depending on the sensing modules (e.g., RGB, multi/hyper-spectral imaging, thermal imaging, and LiDAR) used, UAS-based systems have demonstrated success in measuring traits related to plant morphology (e.g., plant height and volume) [17, 21], physiology [10], stresses [1], crop yield [15, 38], and crop quality [27, 33]. Particularly, many off-the-shelf UAS-based systems have been well integrated with RGB, multi-/hyper-spectral, and thermal imaging modules, which allow non-engineering experts to readily utilize these new tools for collecting needed raw data in research fields and production farms [14, 29, 35]. Therefore, recent interests and efforts have been concentrated on the development of data analytical methodologies and processing pipelines to extract and interpret important crop traits from raw data collected by UAS systems, leading to new biological and agronomic findings and precision management practices. On the other hand, two major engineering needs have been identified for UAS in agriculture: (1) multimodal sensing UAS for agricultural applications and (2) coordinated multi-agent UAS for agricultural sensing [14]. The two needs are related to the design of UAS control and data acquisition.

A large body of literature has focused on the design and control of quadcopters, a representative multirotor, because of the dynamics and diverse military and civilian applications [3, 11, 20, 23]. The control and mechatronics of multirotors (or other types of UAS) are continued research topics, but recent interests have shifted towards multi-agent UAS control [4, 28, 31], operation safety [22], and visualization [22, 34]. The design and control of quadcopters have been gradually formalized in the past decade, which has led to two main options: (1) commercial products via representative manufacturers such as DJI Inc. and (2) open-source solutions via large community supports such as PX4 Autopilot. Both options provide software development kit (SDK) and/or predefined interfaces to enable the customization of UAS systems for various domain applications such as digital agriculture. The key difference between the two options is the balance between guaranteed performance and modification flexibility. Development of data acquisition system for UAS (especially multirotors) has been largely overlooked because of well-integrated commercial products and/or the use of single sensors. Most studies on the development of UAS data acquisition system have reported custom computer programs to control a particular instrument, which lacked the expandability to new sensors with different hardware/software interfaces [7, 8]. Several pioneering attempts, however, have reported the design of new data acquisition system for UAS with either flexible control synchronization [6, 25] and/or multimodal sensing capabilities [16, 36]. In particular, two of them reported the use of robot operating system (ROS)-based solutions [6, 36]. A major limitation of the two studies is the lack of an abstract framework to guide the design and development of ROS-based data acquisition systems which enable multimodal and multi-agent UAS sensing in future agricultural applications.

This chapter aims to provide a conceptual framework for the design and development of a ROS-based data acquisition system for UAS systems in digital agriculture. Basic concepts of ROS components and examples of using ROS for both commercial and open-source UAS systems are provided. A case study of using the proposed framework is presented for an industrial hemp research. Future development and potential applications are also discussed.

2.2 ROS-Based Data Acquisition System

2.2.1 Basic Concepts and Components in ROS

ROS is an open-source middleware for robots and provides a collection of libraries of fundamental functions for robot development [26]. Although ROS is not an actual operating system (OS), it provides OS-level functions such as hardware abstraction, low-level device control, commonly used functions, message-passing between processes, and stable package management. There are three levels of concepts in ROS: file system, computation graph, and community. While all three are important for the ROS ecosystem, the computation graph level is the focus in this chapter because it is directly related to the development of a ROS-based data acquisition system.

In the runtime, ROS builds a computation graph that enables peer-to-peer connections among individual processes via the ROS communication mechanism (Fig. 2.1). There are three types of communications in ROS: (1) synchronous remote procedure call (RPC), (2) asynchronous data streaming, and (3) global data storage and sharing. The communication approaches are implemented by using various ROS computation graph components which should be briefly introduced prior to the design and development of ROS-based data acquisition. The basic components in a ROS computation graph include Node, Service, Master, Parameter Server, Topic, Message, and Bag.

Node: Nodes are the basic computational processes in ROS. A ROS program usually comprises a collection of nodes with each being dedicated for a particular function to achieve a fine-grained modularity. For instance, a node can be developed to interface with an encoder for robot control uses. All nodes are typically connected via the asynchronous data streaming (publisher-subscriber scheme) to form a com-

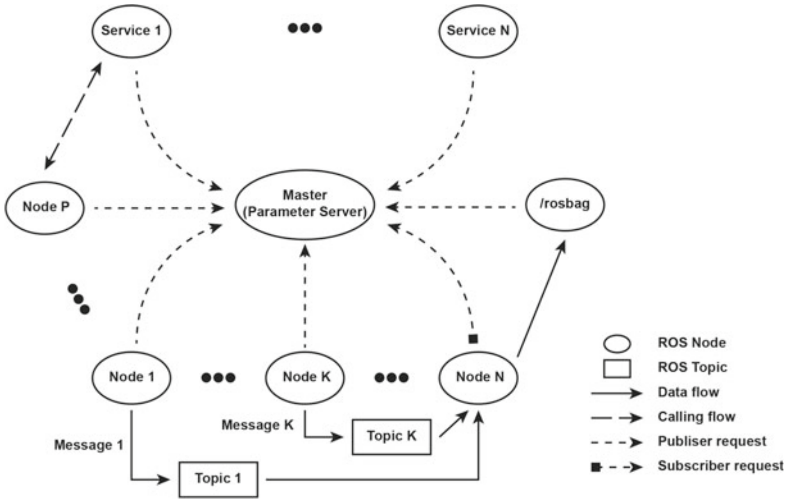

Fig. 2.1 Diagram of key ROS components and their potential connections in a ROS computation graph. It should be noted Node and Service are both processes but use different communication schemes. ROS Master is a naming and registration service to allow the rest nodes and services to identify each other and Parameter Server is a part of ROS Master. Rosbag is the default ROS package to save and retrieve information (e.g., raw data, timestamp, etc.) in the ROS Bag format

putation graph for robot operations such as sensor control and data acquisition. ROS provides two client libraries for the implementation of nodes in C++ (roscpp) and Python (rospy).

Services: Services can be considered as nodes but are defined by a node pair with one for requesting and one for replying. Compared to the publisher-subscriber scheme for one-way communication, the request-reply scheme used by services offers two-way interactions between the paired nodes. This is particularly useful for RPC-style control. It should be noted that one node can advertise multiple services.

Master: The ROS Master is a special service for name registration and identification for the rest nodes and services in a ROS computation graph. Nodes and services should be registered in ROS Master prior to use. Otherwise, they can not be correctly identified and invoked.

Parameter Server: The Parameter Server is a central location in which data are stored by key for global access. Currently, the Parameter Server is a part of the ROS Master for use.

Messages: Messages are simply data structures consisting of fields with various data types. ROS messages support standard primitive types (e.g., integer, floating point, boolean, etc.), arrays of primitive types, and arbitrarily nested structures and arrays. This is very similar to the structs in C programming language.

Topics: Topics are the transportation channels for the publisher-subscriber communication scheme. When they are communicated between nodes, messages are sent out by a publisher node to a topic and then disseminated to all nodes that subscribe to that topic. There is no restriction on the number of topics a node can publish to nor subscribe from. The same topic can also accept multiple publisher nodes concurrently. Thus, topics can be considered as input/output (I/O) buses to support low-latency, many-to-many communications and decouple information production and consumption. This will be particularly useful for data acquisition systems because data streaming errors in one sensor (or one node) would not affect the entire system.

Bags: Bags are a ROS format for message (or data in a general context) storage and retrieval. ROS provides the rosbag package with key functionalities including data recording, bag meta information check, retrieval of (or play back) collected bags, bag compression/decompression, bag file repairing, and so on. It should be noted that rosbag package does not provide a caching mechanism which might be necessary for high-speed, high data volume sensors.

2.2.2 Connecting with Other UAS Components

As a mobile platform, the data acquisition system of a UAS needs communications with the control system of that UAS to coordinate data collection with flight operations. Currently, most UAS platforms use either the DJI control system or Pixhawk-series controllers from PX4 Autopilot. The two control systems have their own ecosystems with different preferred features and development requirements, but both support ROS for secondary development.

The DJI development ecosystem provides an option with a well-integrated ROS environment such as the DJI onboard software development kit (OSDK) (Fig. 2.2). The DJI OSDK provides high-level ROS nodes to communicate with the drone and associated payloads such as cameras and gimbals that follow DJI protocols. These high-level ROS nodes can be used for time synchronization, obtaining drone status, flight control, motion planning, information management, and so on. Additionally, the OSDK also provides interfaces with other DJI SDKs such as payload SDK and mobile SDK for better system integration and development. Since the OSDK ROS is naturally built upon a specific ROS distribution (or version), it supports all packages for that ROS distribution as well. Therefore, a data acquisition system can be quickly developed and integrated with DJI drones for custom data collection needs. For instance, continuous data collection would be configured for imaging sensors (e.g., RGB cameras) with a high shutter speed, whereas a ‘stop-acquire-go’ mode would be set for point-based sensors (e.g., spectrometers) that need a hover for repeated measurements and/or an extended long exposure.

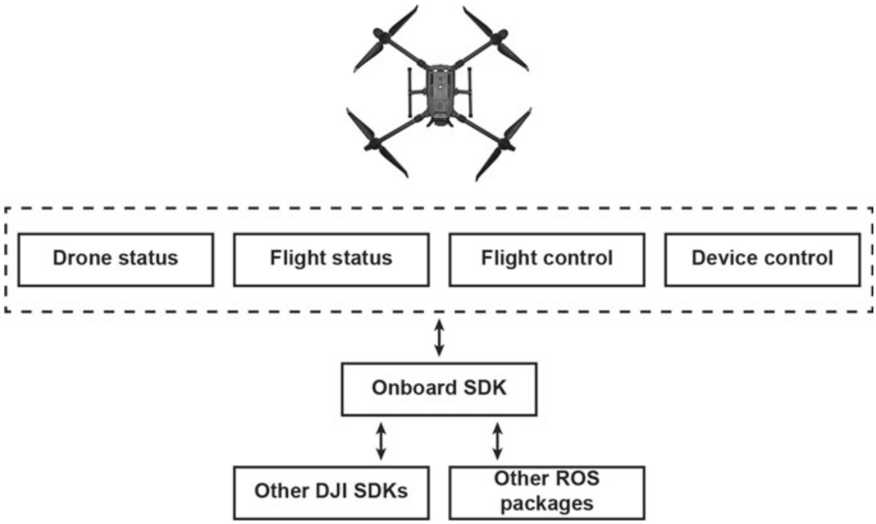

Fig. 2.2 Diagram of the DJI Onboard SDK (OSDK) and interfaces to other SDKs and ROS packages. Functions in the dashed-line rectangle are high-level ROS nodes in the DJI OSDK for drone information acquisition, flight status check, and flight and payload controls. Other DJI SDKs include mobile SDK for embedded systems (e.g., Androids and Apple iOS) and payload SDK for DJI-certified accessories and sensors (e.g., gimbals and cameras). DJI offers a version of OSDK built upon ROS and naturally supports all ROS packages for development

The PX4 Autopilot ecosystem offers a full-stack solution consisting of open-standard hardware controllers (i.e., Pixhawk-series controllers) and open-source control software (i.e., PX4) and ground station (i.e., QGroundControl) (Fig. 2.3). The PX4 control library is designed for all types of unmanned vehicles and provides more functionalities. For drone-related functionalities, PX4 is very similar to the DJI counterpart. Compared with the DJI OSDK, PX4 is not built upon ROS but has robotics application programming interfaces (APIs) to support the use of common robotics libraries such as ROS. It is noteworthy that PX4, as an open-source community solution, tends to be forward-looking and recommends either MAVSDK, the library from the PX4 Autopilot ecosystem, or ROS2, the newly-designed ROS system with new features such as the support of realtime operations. PX4 still supports ROS for the compatibility consideration. Therefore, a ROS-based data acquisition system can be used interchangeably between the two UAS ecosystems. Some minor modifications might be needed to accommodate differences due to various ROS distributions.

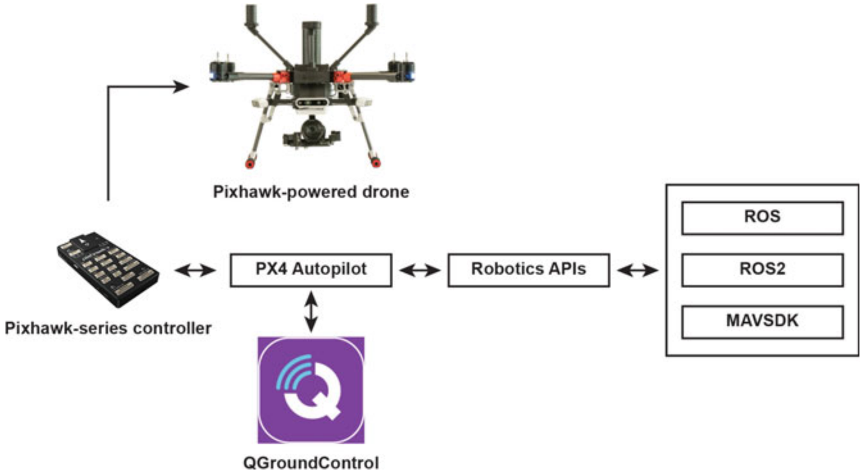

Fig. 2.3 Diagram of the PX4 Autopilot ecosystem including PX4, Pixhawk-series hardware controllers, and QGroundControl ground station. PX4 is a stack of autopilot control functions (i.e., software) for unmanned aerial, ground, and marine vehicles. PX4 provides robotics application programming interfaces (APIs) to facilitate the development of any PX4-powered robots for domain applications without considering all design details. Compared with the DJI ecosystem, PX4 Autopilot ecosystem supports more robot middlewares such as ROS, ROS2, and MAVSDK

2.2.3 Examples for Representative Sensors

UAS systems can carry a wide range of sensors. Based on the sensing principles, sensors can be categorized as optical, electrical, mechanical, acoustic, and so on. Based on the sensing modes, sensors can be grouped as imaging sensors (e.g., RGB, multi-/hyper-spectral, thermal cameras) and point-based sensors (e.g., spectrometers, environment sensors, and volatile organic compounds (VOC) sensors). From the data acquisition perspective, all these sensors can be divided into two categories: sensors have onboard data acquisition and sensor have no onboard data acquisition. The two types of sensors need different designs for ROS-based data acquisition.

Sensors without onboard data acquisition: Many commonly used sensors (e.g., spectrometers and industrial cameras) do not provide onboard data acquisition support because of the design complexity and cost requirements. Integrating these sensors need a data acquisition system not only perform sensor control but also data transfer from a sensor to a UAS-companion computer for storage, process, and visualization. As data streaming is needed and data transfer can be non-synchronized, ROS Node is the most proper option (Fig. 2.4). One node should be developed to control one sensor including sensor initialization, data streaming (i.e., topic registration and publishing), and error handling. A finite state machine (FSM) has been proposed to streamline important events that a sensor node should consider implementing in practice (Fig. 2.5). The key of implementing this state machine for a sensor node is to

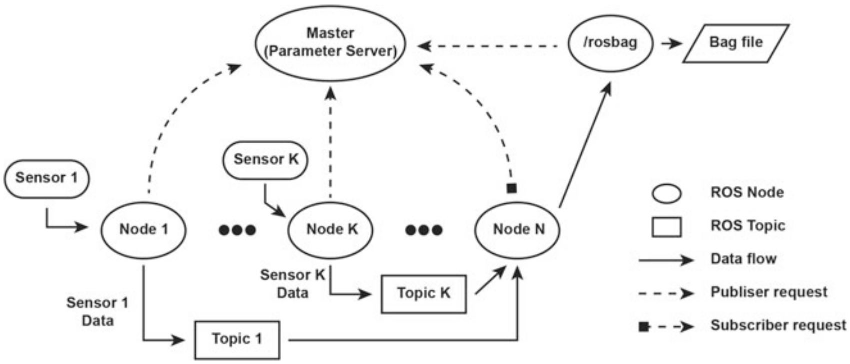

Fig. 2.4 Diagram of a ROS-based data acquisition system with sensor nodes. Each sensor node controls a single sensor for initialization, data streaming, and error handling. Typically, a separate node needs to be developed to subscribe all sensor nodes to gather information together and use the rosbag package for data serialization

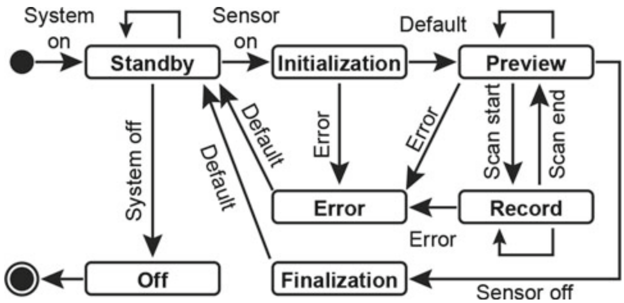

Fig. 2.5 Concept of the finite state machine (FSM) developed for sensor nodes and services to be used in a ROS-based data acquisition system. It should be noted that the implementation of a sensor node and service will be different because of the difference in their communication schemes. A sensor node needs to automate the entire state machine due to the one-way communication, whereas a sensor service can be designed to provide interactive responses to maximize human operator's involvement, especially for error handling

fully automate the state transition based on sensor responses because no interaction will occur with human operators.

An advantage of ROS for data collection is the rosbag library which provides functions in data recording, visualization, check, filtering, compression/decompression, and repairing. However, rosbag does not provide any caching option to accommodate data volume differences among sensors, I/O buses, computer memory, and external storage (e.g., hard drives). Thus, special design needs to be accomplished by developers to avoid potential memory-related issues such as memory leak for sensors with high sampling frequency and data volume.

Sensors with onboard data acquisition: Advanced sensors such as hyperspectral and multimodal cameras usually provide this option to improve data I/O efficiency

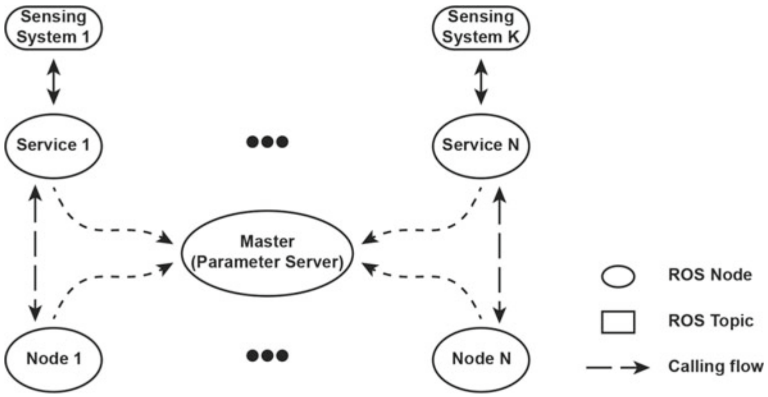

Fig. 2.6 Diagram of a ROS-based data acquisition system with sensor services. Each sensor service communicates with a single sensor via provided sensor control APIs. A corresponding client sensor node needs to be developed to invoke the service for RPC-style sensor control and data collection. Since no data are streamed back to the ROS-based data acquisition system, raw data will be saved in a format predefined by the sensor manufacturer in the onboard device. Also, data visualization through the same ROS environment is non-trivial and may require careful considerations in I/O bandwidth

and overall reliability. Compared with sensors without onboard data acquisition, key differences are (1) data streaming from a sensor to a UAS-companion computer is no long needed and (2) an interactive request-reply communication is required to ensure successful command communications and executions between a sensor and a computer. Therefore, ROS Service is the most proper option (Fig. 2.6). A replying node needs to be developed to communicate with a sensor via APIs provided by the sensor's manufacturer, and a client sensor node needs to be developed to invoke the replying node for various functions. The replying node can register multiple services with each being used for one control function of the sensor, so that the client node can implement the proposed FSM for handling various events based on the sensor running status. No sensor data are transferred from the sensor back to the UAS companion computer, presenting two challenges in the ROS-based data acquisition system. First, raw sensor data will be saved in a format predefined by the sensor manufacturer and may have different meta data information (especially timestamp). A viable solution is to save the ROS timestamp when the data collection request will be confirmed by the sensor service, so that data collected on this sensor can be co-registered with data collected on other sensors and in the UAS companion computer. Second, data visualization through the ROS system will be challenging. An alternative solution is to develop a separate visualization interface to directly visualize data from the sensor's onboard system.

2.3 A Case Study for Industrial Hemp Phenotyping

2.3.1 UAS Data Acquisition System

A custom UAS system was developed by integrating a DJI Matrice 100 platform with a Zenmuse 3 RGB camera (DJI, Shenzhen, China) and a MicaSense RedEdge five-band multispectral sensor (1280×960 px) (MicaSense Inc., Seattle, WA, USA). Based on the framework introduced in the previous section, a ROS-based data acquisition system was implemented to control the two cameras for continuous image collection during a flight. The RGB camera was controlled by using a sensor node and images were saved in ROS bag files, whereas the multispectral camera was controlled by using a sensor service and images with meta data were saved in the onboard SD cards.

2.3.2 Plant Materials and Experimental Design

An experiment was conducted to study the plant morphology contribution to biomass and cannabinoid yield for industrial hemp [5]. Hemp seeds were sown into deep 50-cell Sureroots trays with potting mix (LM111, Lambert, Rivière-Ouelle, QC, Canada) in the greenhouse with supplemental lighting with a 16:8 h light:dark regimen, 3 weeks before planting in the field at Cornell AgriTech (Geneva, NY, USA). The common parent, 'TJ's CBD', was planted from cuttings, but grown in the same greenhouse conditions as the seedlings. Cuttings were rooted using Clonex Rooting Gel (Hydrodynamics Intl., Lansing, MI, USA). At the time of planting (16 June 2020), 15 progeny individuals were randomly selected from each family, and planted together in single plots at 1.2 m spacing within a row and 1.8 m spacing between rows. Granular fertilizer (19-19-19, N-P-K) was incorporated at 95 kg/ha before raised beds with plastic mulch were built. Drip irrigation was installed under plastic mulch. Landscape fabric was installed in aisles to suppress weed pressure. Soil moisture sensors (HOBOnet 10HS, Onset Computer Corp, Bourne, MA, USA) were randomly installed across the field to aid in timing of irrigation. The field was fertigated twice through a Dosatron (Dosatron Intl., Inc., Clearwater, FL, USA) 4 and 6 weeks after planting, using Jack's 12-4-16 Hydro FeED RO (J.R. Peters Inc., Allentown, PA, USA).

2.3.3 Data Acquisition and Ground-Truth Measurements

The developed UAS system was flown 10 times during the growing season using the DroneDeploy App version 2.90.0 (DroneDeploy, Sydney, Australia). Flights were completed at 10 d intervals from 15 days after planting (DAP) to 93 DAP, with an altitude of 20 m and 80% front and side overlap. Ground sampling distances for the Zenmuse 3 and RedEdge were 0.86 cm/pixel and 1.39 cm/pixel, respectively. Ground control points were manually surveyed utilizing a real-time kinematic Trimble R8s GPS (Trimble Inc., Sunnyvale, CA, USA), and used to georectify the reconstructed data in the universal transverse mercator coordinate system for successive analyses. Field assessment trials were performed to manually collect ground-truth data related to floral phenology, hemp stem growth and canopy morphology, chlorophyll concentration, and biomass [5].

2.3.4 Data Processing Pipeline for Extracting Morphological and Vegetation Traits

A data processing pipeline was developed to analyze collected aerial images for the extraction of morphological and vegetation index traits (Fig. 2.7). Collected color and multispectral images were retrieved from bag files and SD cards and then processed using Metashape Pro version 1.6.0 (Agisoft LLC, Russia) to reconstruct color and multispectral orthoimages and colorized 3-D point clouds. Plant geo-locations were calculated using color orthoimages. A color orthoimage was converted to an excessive green index map then binarized using the Otsu method. Connected component labeling was used to segment individual plants and calculate their center locations. Based on plant centers, bounding boxes of 1.83 m (across row) and 1.22 m (within row) were generated for the localization and segmentation of plants in point clouds and multispectral orthoimages. A significant shift of plant centers was observed between 23 and 34 DAP, so the plant geo-locations and bounding boxes were derived from the color orthoimages on the two days, respectively. The locations and bounding boxes calculated on 23 DAP were used to analyze the data collected on 23 DAP, and those calculated on 34 DAP were used for the rest of data.

In the colorized point clouds, the point cloud of each plant was cropped using the calculated bounding boxes. Random sample consensus (RANSAC) was used to identify the ground plane in the plant point cloud (red points in Fig. 2.7) and separate canopy points (green points in Fig. 2.7) for the extraction of canopy morphological traits: height, projected area, and volume. In the multispectral orthoimages, a circular region with a radius of 0.28 m was defined at each plant center, and seven vegetation indices were calculated using pixels within the region for a corresponding plant. The seven vegetation indices comprise the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), green chlorophyll index (GCI), green normalized difference vegetation index (GNDVI), modified non-linear index (MNLI), modified soil adjusted vegetation index 2 (MSAVI2), and optimized soil adjusted vegetation index (OSAVI).

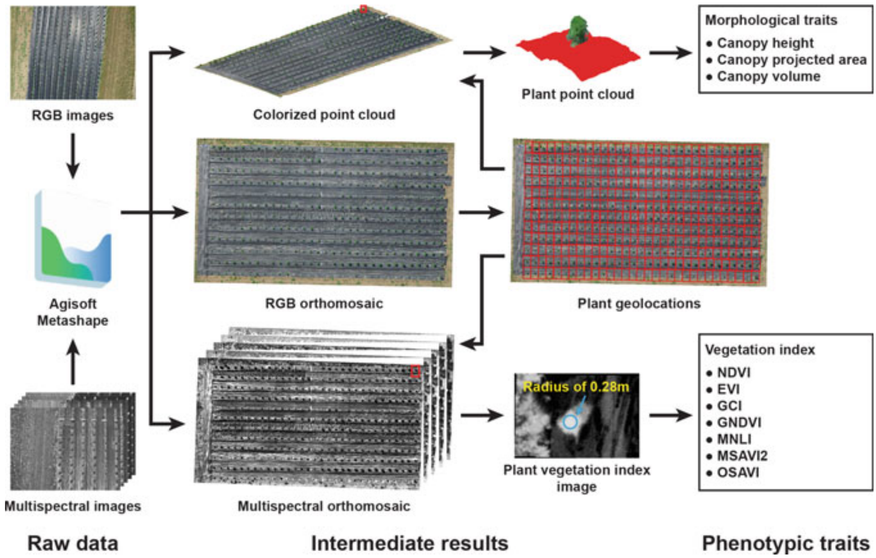

Fig. 2.7 Data processing pipeline for the extraction of phenotypic traits from RGB and multispectral data. Derived vegetation indices include normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), green chlorophyll index (GCI), green normalized difference vegetation index (GNDVI), modified non-linear index (MNLI), modified soil adjusted vegetation index 2 (MSAVI2), and optimized soil adjusted vegetation index (OSAVI)

2.3.5 Measurement Accuracy

There were dramatic differences in morphological HTP aerial measurements (canopy height, area, and volume) between flights flown before and after 56 DAP, with good correlations among measurements within but not among earlier and later flights. These differences were due to a strong windstorm between 50 DAP and 56 DAP that resulted in moderate lodging and stem breakage. Even though F1 families were planted in rows, a family-level analysis did not have a major effect on HTP to field phenotypic correlations of later flights (Fig. 2.8). Canopy height and volume obtained from orthomosaic mesh layers were well correlated with corresponding field-collected phenotype plot height (r=0.83) and kite volume (r=0.67) for early flights. Family-level correlations were even stronger for height (r=0.95) and volume (r=0.80). Biomass yield was most associated with canopy volume (35 DAP) (r=0.56), yet this correlation was only marginally improved on a family mean basis and, for all aerial surveys beyond 50 DAP, there were only weak correlations between the two.

Instances of lodging did not affect vigor or productivity but confounded the accuracy of morphological indices after 56 DAP because of alterations in the primary axis and projected area of individual plots. Physiological indices were likewise affected, but not as profoundly as the morphological indices (Fig. 2.9). There were good phenotypic correlations with nearly all HTP measurements except EVI, which

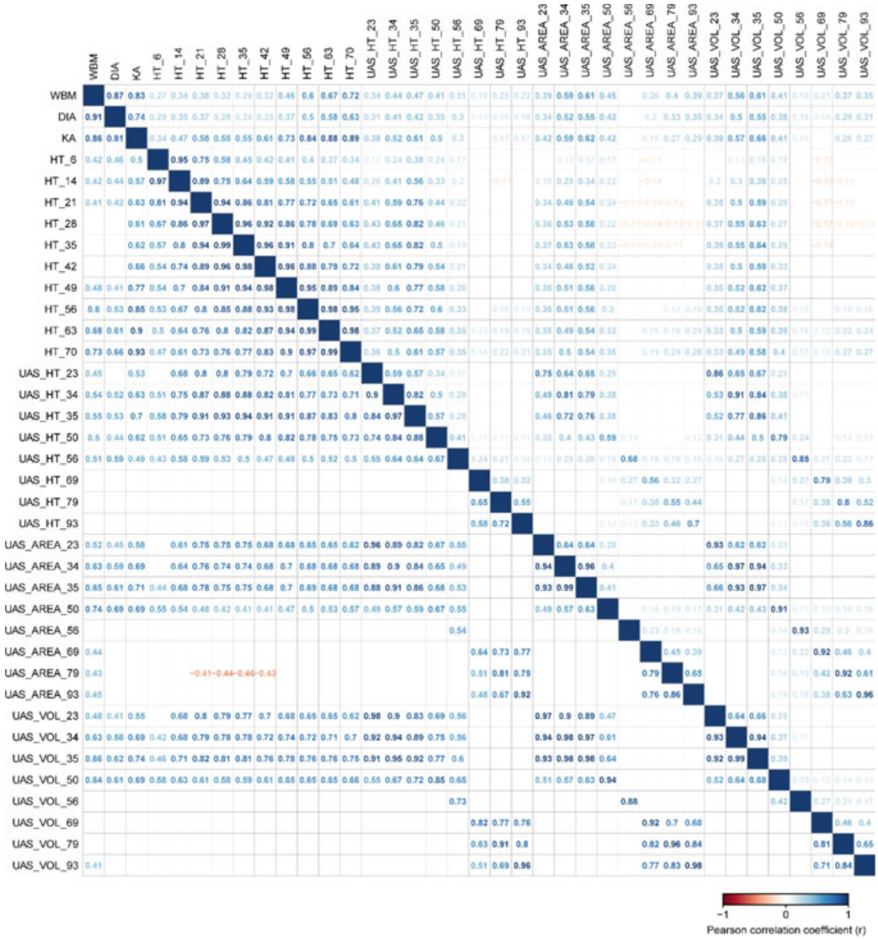

Fig. 2.8 Pairwise correlations of field collected traits with aerial morphological indices on a plot-level (upper triangle) and family-level (lower triangle) basis. The color of coefficients within cells represent significant ($p < 0.01$) positive (blue) or inverse (red) correlations. WBM, DIA, KA, HT, AREA, VOL are for total wet biomass, basal stem diameter, kite branch angle, plant height, plant canopy area, and plant canopy volume, respectively. UAS prefix indicates traits measured using the UAS system

was not informative. Notably, we observed that few cannabinoids were associated with physiological indices (Fig. 2.10). The strongest were in the abundance of the minor cannabinoids cannabicyclol (cannabicyclol; r = –0.35) and cannabidivarin (cannabidivarin; r = –0.17) with MNLI, MSAVI2, and OSAVI at 93 DAP, but those with cannabidivarin may be due to population structure, since only two families had individuals with >1% cannabidivarin content. It may be possible to predict cannabinoid profiles and yield using multispectral or hyperspectral data, similar to what

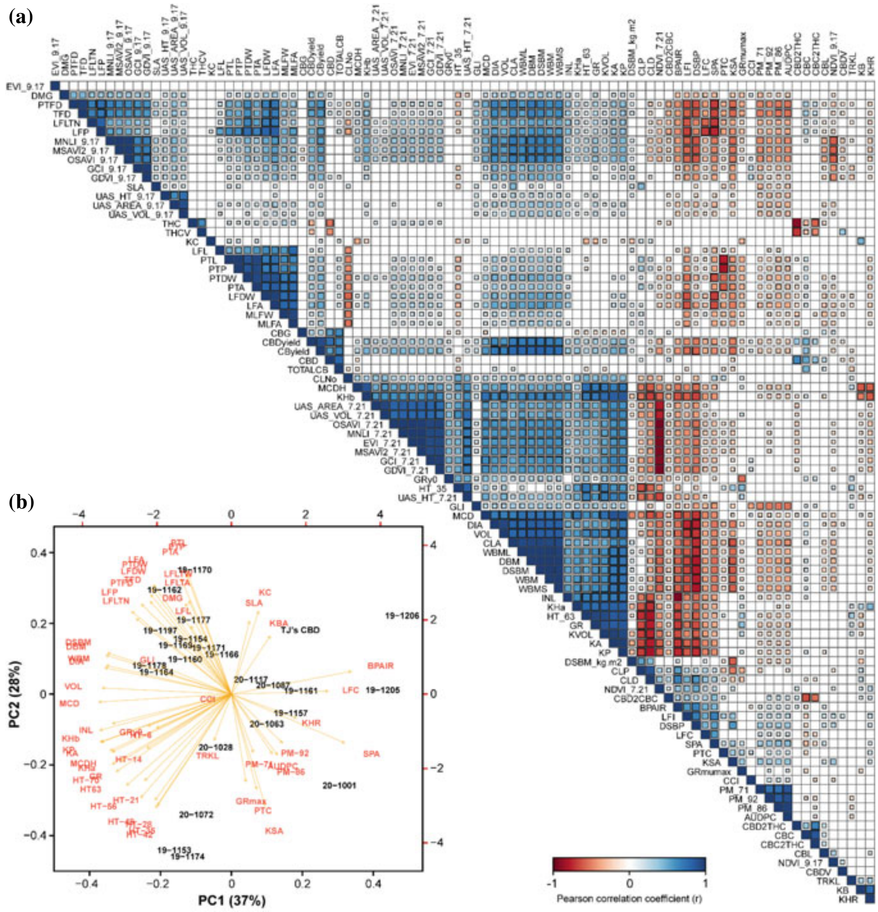

Fig. 2.9 Pairwise correlations of field collected traits. The color of each square in (**a**) represents a significant (p < 0.01) positive (blue) or inverse (red) correlation. The size of each square represents the strength of the correlation. Non-significant correlations (p < 0.01) were not drawn. Traits were ordered via hierarchical clustering (method = "complete"). PCA biplot (**b**) of the same traits (scaled) using family means

has been attempted with Fourier transform near-infrared spectroscopy (FT-NIR), but concerted segmentation of inflorescences would be required to develop an effective strategy to better estimate these profiles from aerial imaging. Further analyses of denser, direct-seeded plantings would both reduce incidence of lodging and offer better estimates compared with the larger plot spacing provided in this trial.

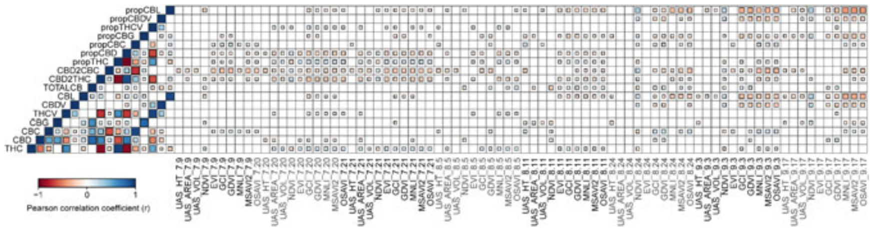

Fig. 2.10 Pairwise correlations of cannabinoid profiles and aerial indices over time. The color of each square in (A) represents a significant ($p < 0.01$) positive (blue) or inverse (red) correlation. The size of each square represents the strength of the correlation. Non-significant correlations ($p < 0.01$) were not drawn

2.4 Discussion

The developed ROS-based data acquisition system showed the capability to handle multiple sensors for collecting aerial images in the field. Sensors attached to the UAS platform were both with and without onboard data acquisition support, showing the ability of the proposed framework for designing new data acquisition systems for UAS platforms.

The case study demonstrated the use of this framework for only two sensors in one system and did not fully attempt all possible needs in the future. Based on a large body of literature in using ROS for UAS control, especially multi-agent UAS control [4, 28, 31], however, it is reasonable to envision the smooth integration of ROS-based data acquisition systems with multimodal sensing modules and/or UAS swarms for agricultural applications in the future. In particular, previous efforts on ROS-based UAS control and motion planning could be reused with minimal modifications for these newly integrated systems. Compared with off-the-shelf solutions and custom data acquisition systems previously developed, the framework in this chapter offers a new paradigm enabling rapid system development, deployment, and testing.

On the other hand, ROS has some major limitations such as no support of real time operations, which has led to the revolutionary development of ROS2. Although ROS2 uses many different design and implementation choices than ROS, it is fortunate that the ROS community provides several ways (e.g., ROS bridge package) to enable the communication between ROS and ROS2 to maximize the code reuse and performance stability. In particular, the use of ROS2 is highly recommended by the PX4 Autopilot community and would receive a strong community support for technical development and testing. In contrast, the DJI ecosystem has a slower pace in adopting newly developed ROS2 and/or other third-party libraries (e.g., MAVSDK) due likely to the compatibility and stability considerations. This may create additional burdens for researchers who may want to simultaneously take the advantages of ROS2 and commercial products with guaranteed performance and reliability.

2.5 Summary

This chapter provides a conceptual framework based on ROS to guide the design and development of data acquisition system for UAS in agricultural applications. By taking the advantage of ROS, the data acquisition system can have desired stability, customizability, modularity, and expandability without special considerations and efforts from developers. The conceptual framework provides implementation examples for sensors with/without onboard data acquisition support, which cover most possible use cases in practice. This will also be crucial for integrating multimodal sensing modules in a balanced data I/O to circumvent possible I/O issues in a central computer. The conceptual framework is expected to be used as a reference guideline for the development of multimodal and multi-agent UAS systems for digital agriculture in the future.

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