UNMANNED AERIAL SYSTEMS IN AGRICULTURE: PART 2 (SENSORS)

FS285E

By
Lav R. Khot, Automation Engineering, Department of Biological Systems Engineering

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Introduction

Traditional crop scouting methods (e.g., visual scouting, field sampling and laboratory analysis) are not rapid especially when conditions affecting the crop are too complicated to be identified using these techniques. Advanced sensor technologies can help in such scenarios.

A sensor is "a device that responds to a physical stimulus such as heat, light, sound, pressure, magnetism, or a particular motion, and transmits a resulting impulse for measurement or operating a control" (Merriam-Webster 2017). Typically, sensor data can be used to detect early signs of biotic (biological in nature) or abiotic (water, solar radiation, temperature, air quality) crop stress. When combined with various sampling methods (i.e., ground or aerial), sensor-extracted data can be useful to farmers for monitoring plant growth and health. It can also help in potential crop yield estimation.

The emergence of unmanned aerial systems (UAS) has enhanced possibilities of acquiring high-resolution multi-spectral (i.e., few spectral bands) images of agricultural fields at a temporal resolution controlled by the user. It can lead to easier and faster monitoring of large farms and agricultural decision making. UAS have evolved into an important technology in precision agriculture with multiple companies and agricultural service providers exploring how to integrate it into production management decision making. Sensors are an integral part of UAS technology for its meaningful and efficient use in agriculture.

Today, a wide range of optical imaging systems are available which can be integrated with UAS. In general, optical sensors are classified based on the form of data acquired and source of electromagnetic radiation (EM) used to measure the response. **Spectrometric** or **imaging** sensors can capture spectral and spatial data about an object (e.g., plant canopy) in the EM radiation ranging from about 300 nm to 30 cm. For example, a simple point-and-shoot digital camera captures EM reflectance from the field-of-view (FOV) in red (650 nm), green (510 nm), and blue (475 nm) bands to form a color image. **Time-of-Flight** (ToF) sensors capture the time taken for the signals to reach an object and provide point cloud time series data describing the object features.

Sensors that capture and record natural EM radiation coming from the sun and reflected from the objects are termed as **passive sensors**. Most optical sensors used in agricultural remote sensing often are of passive type. **Active sensors** are integrated with specific energy source to illuminate the object and record the response. For example, the light detection and ranging (LiDAR) and ultrasonic sensors, respectively, use infrared light and short sound pulses as energy sources to capture ToF data. For example, a LiDAR sensor (from SICK Inc., Germany) emits infrared light (905 nm) in the sensor FOV and measures the response as reflected light intensity with distance.

A range of active and passive sensors can be integrated with small UAS. Georeferenced and processed data from such sensors can be used for decision support in crop management. Overall, the integration of a typical sensor with a small UAS depends on the specific agricultural application and the UAS platform payload lift capabilities. The section on Sensor Types summarizes some of the key sensors that can be integrated with small UAS for agricultural crop sensing.

Sensor Types

Table 1 summarizes the types, working principle, and associated attributes of the sensors. Because the spectrometric and imaging sensors measure reflectance in the visible-near infrared (VIS-NIR 350-2,500 nm) regions of the EM spectrum, they are broadly used for overall biotic and abiotic stress symptom monitoring. A wide range of commercial multispectral (3 to 10 bands) sensors (e.g., RedEdge from MicaSense, WA) that measure reflectance up to 1,000 nm are available for use with UAS. The cost of multi-spectral sensors is primarily governed by the number of spectral bands and the specific spectral range of such bands. One of the major limitations for VIS-NIR-based passive multispectral sensors is that changes in ambient light conditions (variation in incident light intensity) can influence the response (reflectance).

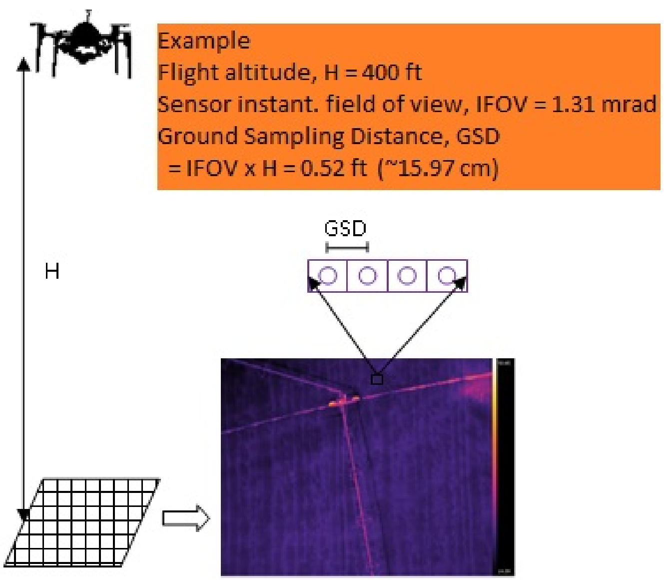

Figure 1. Realization of sensor ground sampling distance.

There are several ways to partly compensate for ambient light changes, which include: (1) use of a reference calibration panel for data normalization (e.g., Spectralon Diffuse Reflectance Panel), (2) use of incident light sensors (e.g., down welling light sensor from MicaSense, WA) integrated with the VIS-NIR sensing module to account for the variation in solar light intensity, and (3) utilization of spectral ratios or vegetation indices rather than use of absolute reflectance values. Note that sensor ground sampling distance (GSD, center-to-center spacing of ground projections of sensors instantaneous FOV [Grant 2016]) at given flight altitude governs the acquired image resolution and hence object discrimination ability (Figure 1). The smaller the GSD, the higher the object discrimination ability will be (i.e., spatial resolution).

The hyperspectral imaging (HSI) sensors having narrow spectral resolution ideally allows more detailed soil and crop analysis in the ranges of 380 to 2,500 nm. Existing HSI sensors used in proximal and aerial sensing applications are of line scan (push broom) type (i.e., either the sensor or the object need to be moved to record or capture the image). Such sensors are somewhat heavy to be fitted on small UAS. Moreover, HSI data output (also called “hypercubes”) need significant storage and computational power. In recent years, however, snapshot-type (similar to digital camera) HSI sensors that generate an instantaneous image of the objects within the FOV are being designed for UAS-based remote sensing applications. Hyperspectral sensors can provide a higher level of reliability to detect early signs of crop stress compared to general multispectral sensors. However, their form factor, payload and cost needs to be commercially viable for broader adoption by agricultural community.

Sensor/Type	Spectral Range /Bands	What is Measured	Limitations
Digital Cameras (Imaging, Passive)	VIS reflectance (380-700 nm) Red, Green, Blue	Gray scale or color images	– Limited visual spectral bands and properties
Multispectral (Imaging, Passive)	VIS-NIR reflectance (380-1000 nm)	Few bands for each pixel in spectral range	– Limited to few spectral bands
Hyperspectral (Imaging, Passive)	VIS-NIR reflectance (380-2500 nm) Narrow bands result in high spectral resolution	Continuous or discrete spectra for each pixel in spectral range	– Cost, payload – Extracting information from images remains a challenge
Thermal (Imaging, Passive)	Infrared emission (7-14 µm)	Pixelated temperature (for sensor with radiometric calibration)	– High resolution cameras have heavy payload
LiDAR (Time-of-Flight, Active)	Specific band in VIS-NIR (e.g., 1,064, 1,550 nm)	Physical measurements within laser time-of-flight (distance, reflectivity)	– Cost, payload – Sensitive to small variations in path length

Table 1. Major types of sensors used for small UAS-based agricultural remote sensing.

Thermal imaging sensors capture an object's long wave infrared radiation using thermal detectors (i.e., microbolometers). In terms of data output, sensors with radiometry-enabled options need to be used for acquiring pixelated temperate within the FOV. Thermal imaging sensor's form factor and cost are decreasing rapidly and options exist when it comes to integrating such technology with small UAS. The sensors, however, still need to be improved for acquiring high resolution and noise-free data.

Data Analytics Solutions

Depending on the VIS and NIR bands available in the multispectral and HSI sensors, a wide range of vegetation indices (VIs) representing broad and narrowband greenness, light-use efficiency, nutrient levels, and water-use efficiency can be estimated.

The normalized difference vegetation index (NDVI) is a commonly used vegetation index representing a ratio of sensor reflectance in red (R) and near-infrared (NIR) bands (NDVI = [NIR-R] / [NIR+R]). It represents overall crop health and can range from -1 (stressed) to 1 (healthy crop).

Details on other spectral band specific vegetation indices used in agricultural crop monitoring can be found at http://www.exelisvis.com/docs/VegetationIndices.html. For example, normalized difference nitrogen index (NDNI) can be useful in crop nitrogen nutrient level evaluation; photochemical reflectance index (PRI) can be useful in canopy photosynthetic activity or light use evaluation, and normalized difference infrared index (NDII) can express crop water stress. Existing portable and affordable multi-spectral sensors that capture reflectance data in less than a 1,000 nm range often limits the extraction of stress specific vegetation indices.

Table 2 summarizes a list (not all inclusive) of available commercial data analytic solutions. Options range from procuring software to do offline, post-flight data processing through in-house technical expertise to the cloud-based data upload for storage, online and offline external data processing, and presentation. Besides commercial software, ImageJ (from NIH.gov) and QGIS (QGIS.org) are the open source data analytic software available for small UAS-based data processing. Growers often have concerns about the use of online cloud-based services due to issues of data ownership, privacy, and unintentional or without consent sharing of their field data by such providers.

Software/ Provider	What is Offered
ATLAS MicaSense, Inc. Seattle, WA	– Cloud-based processing, storage, management, and presentation – Sensors supported: only commercialized by MicaSense (imaging type) – Cost: $/acer, or $/month
Pix4D Mapper Pix4D Inc. San Francisco, CA	– Online/offline/cloud-based processing and sharing – Sensors supported: most of all (imaging type) – Cost: $/month, $/year or one time
Drone2Map for ArcGIS Esri, Redlands, CA	– Similar function as of Pix4D Inc. – Cost: $/year or one time
ENVI Harris Geospatial Inc. Melbourne, FL	– Online/offline/cloud-based processing and sharing – Sensors supported: most of all (imaging and non-imaging type) – Cost: $/year or one time

Table 2. Commercial data analytic solutions for small UAS-based remotely sensed data (list includes a few representative examples and is not all inclusive).

Future of UAS-Based Remote Sensing

Figure 2 illustrates potential agricultural applications using pertinent sensor types. Optical sensors such as RBG, multispectral, hyperspectral, thermal infrared, and LiDAR can provide helpful information on crop growth and health. Because of their low cost and ease of image interpretation, multispectral sensors have been by far the most commonly used in UAS-based agricultural applications (Zhang and Kovacs 2012). For example, they have been used for crop health monitoring in vineyards (Candiago et al. 2015), sugar beets, potatoes (Sugiura et al. 2016), and soybeans. They have also been explored for crop emergence (wheat and cotton) (Khot et al. 2016; Chen et al. 2017) and yield estimation in range of irrigated crops (Sankaran et al. 2015). UAS-integrated multispectral sensors have also been used for detection of nutrient deficiencies in corn, wheat, soybeans, and for weed identification in field crops. More detail on the applications of the sensors are summarized in Sankaran et al. (2015).

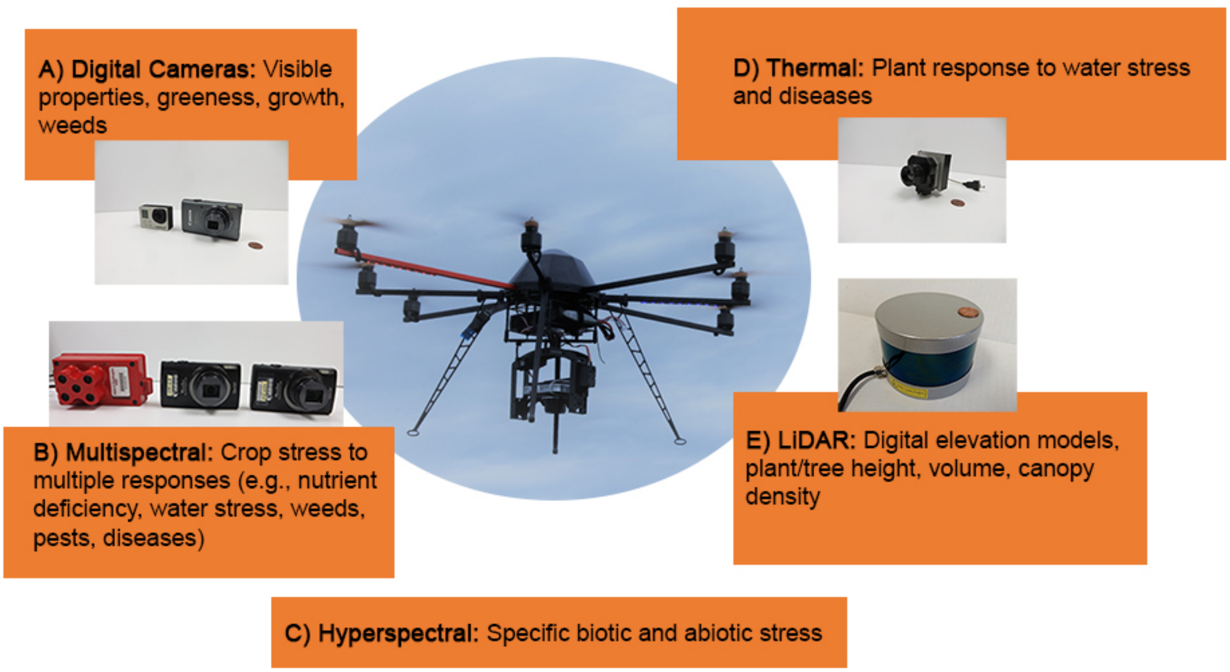

Figure 2. Realization of agriculture applications using specific sensors integrated with UAS. Sensors shown are example commercial units procured and used in our ongoing research.

As agricultural industry explores this domain, sensors for specific agricultural applications would require major validation efforts under various scenarios using ground-reference methods. It applies specifically to the crop monitoring solutions offered by a range of agricultural service providers. Variation in sensor response during the crop season due to various climatic and non-climatic conditions need to be accounted for before using such data for production management decision making.

In general, with the availability of commercial small UAS platforms that are rugged, reliable (in-flight operations), and are versatile (in terms of payload handling), major efforts are needed towards the development of sensors that have (1) a small form factor, (2) light weight, (3) larger field of view, (4) versatility of triggering mechanisms, (5) optimal image capture rate for adequate image overlap, (6) easy calibration procedures/mechanisms, (7) on-board data storage capability, (8) less power consumption rate, and (9) field ruggedness.

Conclusion

Overall, the domain of imaging sensors with small UAS integration capability is changing rapidly in terms of capabilities and cost. Major validation of these sensors for specific agriculture application are needed for meaningful use in agricultural crop production management. Industry also needs to develop and offer robust data analytics solutions for processing of sensor data to have intelligence available to grower for real-time crop management decisions.

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Additional Resources

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