

RoboWeedSupport-Semi-Automated Unmanned Aerial System for Cost Efficient High Resolution in Sub-Millimeter Scale Acquisition of Weed Images

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Abstract—Recent advances in the Unmanned Aerial System (UAS) safety and perception systems enable safe low altitude autonomous terrain following flights recently demonstrated by the consumer DJI Mavic PRO and Phantom 4 Pro drones. This paper presents the first prototype system utilizing this functionality in form of semi-automated UAS based collection of crop/weed images where the embedded perception system ensures a significantly safer and faster gathering of weed images with sub-millimeter resolution. The system is to be used when the weeds are at cotyledon stage and prior to the harvest recognizing the grass weed species, which cannot be discriminated at the cotyledon stage.

Keywords—Weed mapping, integrated weed management, DJI SDK, automation, cotyledon plants.

I. INTRODUCTION

TODAY UAS (addressed as drone in the following) are being used worldwide for weed mapping. Patches of weed are easy to identify using centimeter pixel resolution and relatively simple algorithms [1]-[3]. However, to identify and classify weeds at the cotyledon stage using shape features [4]-[6], millimeter and sub-millimeter pixel resolution is needed [7], [8].

Jørgensen et al. [9] demonstrated off-the-shelf drone as a user-friendly platform for obtaining high-resolution (sub-millimeter ground sampling distance) images as input to automated weed recognition data processing. Weed mapping is conducted as low altitude (sub-meter) point sampling in field hot spots, such as headlands, depressions in the terrain, etc. However, Jørgensen et al. [9] point out that collecting images from sub-meter altitudes is not cost efficient, when using manual control of the drone, especially in uneven and undulated fields.

In contrast to classic drone flight planning with the purpose of making orthographic maps from >20 m altitudes, semi-automated weed mapping requires a special flight planning tool for controlling the drone. This tool should include an interface in which the user easily can point and create

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waypoints where the drone should collect images. Drone behavior, such as flight speed, image capture altitude, camera settings, etc. should be automated.

In this work, flight altitude is controlled by an active height sensor embedded on a consumer drone with no retrofits. The only required input from the pilot is to decide numbers and locations of waypoints, and to avoid obstacles in the flight plan due to the low altitude flying. The remaining flight control and image capturing are fully automated.

The system is expected to be used as a data collection platform in weed mapping systems, while the weeds are at the cotyledon stage [10]. Weed recognition and classification in the collected images will be handled by a separate software.

II. MATERIALS AND METHODS

The aim is to use a consumer drone with an active height sensor and Software Development Kit (SDK) availability. Experience from Madsen et al. [11] showed that the ultrasonic height sensor of the Phantom 4 (DJI, Shenzhen, China) drone was proven to be too unreliable to be used for actively adjusting the flight height. Instead, a DJI Matrice 100 (DJI, Shenzhen, China) retrofitted with a Velodyne VLP-6 LiDAR (Velodyne LiDAR, Morgan Hill, USA) had to be used. However, this solution is expensive and not suited for consumers. Hence, a DJI Phantom 4 Pro (DJI, Shenzhen, China) drone is chosen as case demonstrator in this study.

A. Mechanical Setup

The entire setup consists of an iPad Air (Apple Inc., California, USA) that communicates with a DJI Phantom 4 Pro drone through the corresponding remote controller, see Fig. 1.



Fig. 1 Illustration of the iPad with running application and the DJI Phantom 4 Pro Drone after successful mission completion. Picture taken during test of the system on February 6, 2017

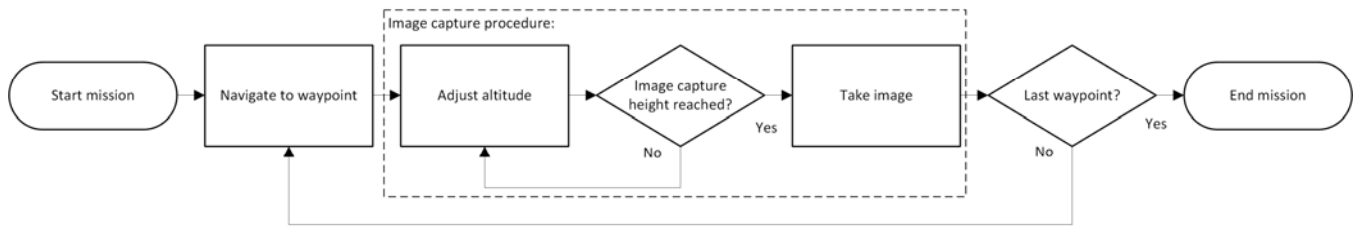


Fig. 2 State chart of mobile application during mission execution. The chart show how the application toggles between navigating to waypoint and the 'Image capture procedure'



Fig. 3 Images acquired during test of the system performed February 6, 2017 and uploaded to the RoboWeedSupport cloud as described in details by Rydahl et al. [16] The images are plotted corresponding to the location they were taken

The Phantom 4 Pro drone is configured with the default accessory package, with exception of the battery that has been replaced by the Phantom 4 Series – Intelligent Flight Battery (5870 mAh, High Capacity) (DJI, Shenzhen, China), to ensure a longer flight duration. The Phantom 4 Pro drone is chosen as the platform, since it includes a better safety system and ultrasonic height sensor, compared to the older versions in the Phantom series. The improved ultrasonic height sensor provides a reliable height measure that is used throughout mission execution to make altitude adjustments.

In order to ensure sufficient resolution, the image acquisition height was set to 1 m. This results in an imaging area of $\sim 1.12 \text{ m}^2$ and $\sim 4 \text{ pixels mm}^{-1}$.

B. Mobile and Tablet Application

An iPad with iOS operating system is used as the application host. The iOS application handles route planning and is responsible for the image capture procedure. The iOS application is developed in Objective-C using Xcode (Apple Inc. California, USA) and the DJI mobile SDK (DJI, Shenzhen, China). The application is based on the DJI tutorial, 'GSDemo' [12] and is modified, so each time a waypoint is reached, the application starts a custom implemented image capture procedure. This procedure consists of two processes: 'Adjust altitude' and 'Take image'. The flow of the waypoint mission is shown in Fig. 2.

The waypoint mission component does not incorporate the height measures from the active height sensor on the Phantom 4 Pro and is therefore not suited nor able to control the drone close to the ground (safety system interferes at 2 m above ground and below). Instead, the 'Adjust altitude' process stops the waypoint mission temporarily, and the iPad application takes direct control of the drone through the virtual joystick component. The process is implemented as a control loop that uses the ultrasonic sensor of the Phantom 4 Pro to adjust the vertical velocity of the drone with an update frequency of 10 Hz. The adjustment is implemented as a linear function of the difference in current and desired height, so the drone decelerates as it comes closer to the image capture height.

When the drone is within $\pm 0.1 \text{ m}$ of the desired image capture height, the 'Take image' process is executed. The process will take an image of the ground and will resume the waypoint mission. When resuming the mission, the flight and image capture altitude are adjusted to compensate for height variations in the field.

III. RESULTS

Fig. 3 shows the images acquired during a test of the system performed February 6, 2017 at 1:50 pm. under cloudy and relatively dull conditions and fixed ISO (= 400) resulting in exposure times of 1/250 to 1/120 second. The test flight was performed in a winter wheat field in eastern Jutland, Denmark

(56°12'11.8"N, 10°09'01.8"E). The images are plotted on a map to show the location in the field where they are captured. Because of the low altitude, the down force from the drone

rotors created motion blur in the images, in particular for the winter wheat leave tips. This was not the case in most of the weed cases due to their close to ground posture.

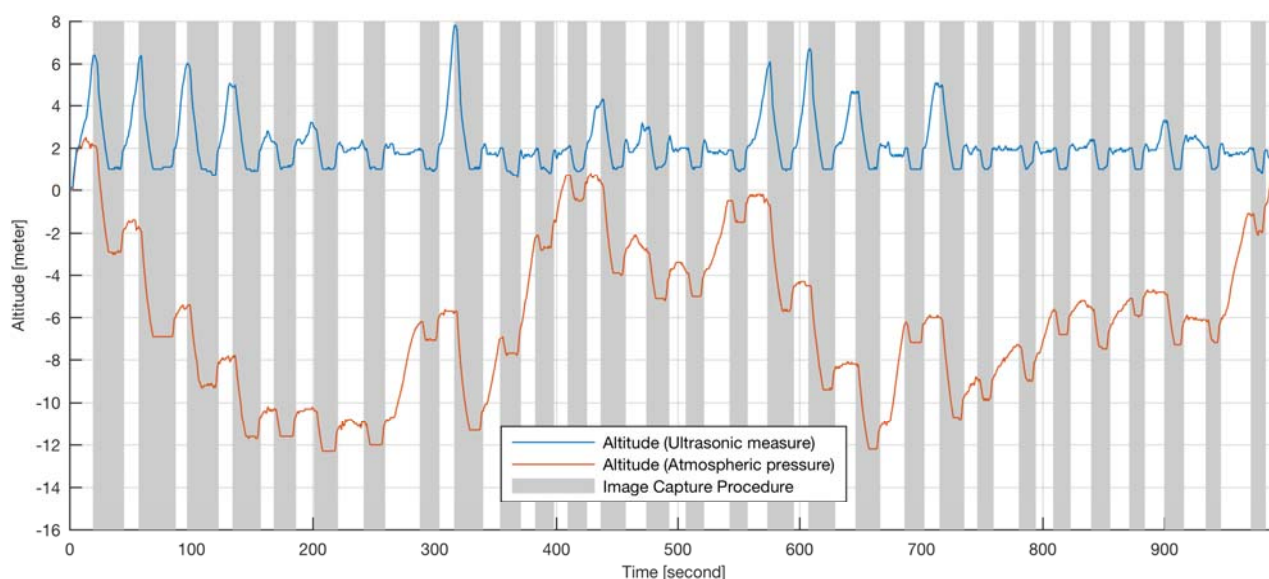


Fig. 4 Recorded altitude measures of the drone during test flight February 6, 2017. The ultrasonic altitude shows the operational flight height relative to the ground throughout mission execution. The atmospheric pressure altitude shows the flight height relative to the home position and gives an indication of the variations in the terrain. The areas highlighted in gray indicate the time used in the image capture procedure, whereas the remainder is used on take-off, navigation between waypoints and end mission action. The plot shows how the software adapts the flight and capture altitude to height differences in the field

From pressing “start mission” within the app shown in Fig. 1 on the tablet until the Phantom 4 Pro landed again, the drone operator did not touch the remote control or intervened in any way until the drone landed again 17 minutes later. This was a huge relief compared to manually collecting sub-meter images with a DJI Phantom 4 as demonstrated by Jørgensen et al. [9].

Table I summarizes key numbers from the test flight on February 6, 2017. The numbers show that the system has a capacity of ~ 2 images min^{-1} , with an image density of ~ 5 image ha^{-1} . The table shows that the image capture procedure is highly time consuming, which is also apparent by plotting the recorded altitude of the drone throughout the test flight, see Fig. 4.

TABLE I
 KEY NUMBERS FROM TEST OF THE SYSTEM PERFORMED ON THE FEBRUARY 6, 2017

Parameter	Value
Number of images	29
Set Flight altitude	2.2 m
Set Image capture altitude	1 m
Total flight time	1028.1 s
Area covered	~ 6 ha
Distance traveled	~ 1900 m
Mean time per image (navigation to waypoint + image capture procedure)	34.0 ± 4.9 s
Mean time image capture procedure	18.4 ± 4.5 s

The 29 images were analyzed through manually annotation and automated software for detection of weeds as presented by

Dyrmann et al. [13]. The manual annotation was able to register 851 occurrences of weeds, whereas the automated software was able to register 329 occurrences from the images. An example of the results from the automated weed detection is shown in Fig. 5.

The detected weeds were also attempted classified using a modified version of the automated classifications software presented by Dyrmann et al. [5]. However, the classification did not provide any useable results, since the quality of images is too low, due to the poor weather conditions.

IV. DISCUSSION

This study has demonstrated that consumer drones are capable of being used for semi-autonomous image acquisition with resolution in sub-millimeter scale. However, experience from the test of the system has shown two issues that will need to be handled in future versions of the system: The image quality, and the overall capacity of the system with respect to area covered versus time spent.

The quality of the images recorded during test of the system on February 6, 2017 is sufficient for detection of weeds, but is not good enough for classification of the weeds. The poor image quality is probably a result of the cloudy and relatively dull weather conditions. The experienced image blur could also be an effect of the relatively high ISO resulting in the camera grouping pixels together to capture more light. This issue should be relatively easy to fix, since it only requires better planning with regard to the weather and other camera settings on the drone.



Fig. 5 Results from using the automated weed detection software presented by Dyrmann [13]. The red squares show the locations where the weeds are detected. The figure also shows that the detection is not perfect, since it fails at detecting some weeds

It is not surprising that approximately half of the flight time is used on the image capture procedure as seen in Fig. 4 and Table I, since the procedure is not fully optimized. Pausing the waypoint mission, descending and ascending the drone and resuming the mission are all very time consuming, since it depends on off-drone remote control on the iOS-based iPad. If this procedure was embedded in the drone's flight controller as part of the DJI SDK, the time could probably be reduced. Still the capacity of the drone-based system in this work is rather low compared to the ATV based weed mapping solution described by Laursen et al. [14]. Assuming the drone-based system manages to decrease the time of the image capture procedure by a factor two and the flight time is increased to 30 minutes (maximum flight time listed by DJI [15]), then approximately 73 images of 1.12 m² equal to ~82 m² of the field can be imaged in one flight. The image area of the ATV system presented by Laursen et al. [14] is approximately quarter compared to solution presented in this work, but ~1400 images are collected in half an hour covering 14 hectares resulting in 350 m² of the field imaged. The ATV solution is estimated to be a 20,000 EUR investment, whereas the solution presented in this study is estimated to approximately 2,200 EUR. This leaves plenty of room for

investing in several consumer drones and reaching the same or higher capacity than the ATV solution. In addition, the drone does not create tracks in the fields. Assuming that future low cost consumer drones can fulfill the latter capacity improvements, it will be a valuable tool in agriculture if linked up with analytics systems, e.g. the RoboWeedSupport cloud system described by Rydahl et al. [16].

The results presented by Madsen et al. [11] show that it could be beneficial to use the latest Normalized Difference Vegetation Index (NDVI) map as a reference, when planning the spatial distribution of the image acquisition points prior to flight. This could be implemented by adding the NDVI as a layer on top of the map in the iOS application. Since the Sentinel-2 and Landsat satellite imagery is free and relatively easy to access, e.g. ESA Scientific Hub, Amazon AWS, Google Cloud Platform [17], [18], this feature will be implemented in future version of the software developed in this work.

V. CONCLUSIONS

In conclusion, consumer drones like the DJI Phantom 4 Pro can be used for autonomous image acquisition with sub-millimeter pixel resolution. However, there are rooms for

improvements for the proposed solution, such as further increasing the quality of the acquired images and optimizing the flight control, in order to increase the capacity of the system. In order to become a truly valuable weed mapping tool, the system should ideally be linked with fully automated weed recognition software and integrated weed management decision support systems.

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REFERENCES

- [1] J. M. Peña, J. Torres-Sánchez, A. I. de Castro, M. Kelly, and F. López-Granados, "Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images," *PLoS One*, vol. 8, no. 10, p. e77151, 2013.
- [2] D. Gómez-Candón, A. I. De Castro, and F. López-Granados, "Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat," *Precis. Agric.*, vol. 15, no. 1, pp. 44–56, 2013.
- [3] J. M. Peña, J. Torres-Sánchez, A. Serrano-Pérez, A. I. de Castro, and F. López-Granados, "Quantifying Efficacy and Limits of Unmanned Aerial Vehicle (UAV) Technology for Weed Seedling Detection as Affected by Sensor Resolution," *Sensors*, vol. 15, no. 3, pp. 5609–5626, 2015.
- [4] M. Dyrmann and R. N. Jørgensen, "RoboWeedSupport: weed recognition for reduction of herbicide consumption," in *Precision agriculture '15*, J. V. Stafford, Ed. Wageningen Academic Publishers Books, 2015, pp. 571–578.
- [5] M. Dyrmann, H. Karstoft, and H. S. Midtiby, "Plant species classification using deep convolutional neural network," *Biosyst. Eng.*, vol. 151, pp. 72–80, Nov. 2016.
- [6] M. Laursen, R. Jørgensen, H. Midtiby, K. Jensen, M. Christiansen, T. Giselsson, A. Mortensen, and P. Jensen, "Dicotyledon Weed Quantification Algorithm for Selective Herbicide Application in Maize Crops," *Sensors*, vol. 16, no. 11, p. 1848, 2016.
- [7] R. B. Brown and S. D. Noble, "Site-specific weed management: sensing requirements-- what do we need to see?," *Weed Sci.*, vol. 53, no. 2, pp. 252–258, 2005.
- [8] D. E. Guyer, G. E. Miles, M. M. Schreiber, O. R. Mitchell, and V. C. Vanderbilt, "Machine vision and image processing for plant identification," *Trans. ASAE*, vol. 29, no. 6, pp. 1500–1507, 1986.
- [9] R. N. Jørgensen, M. S. Laursen, M. Dyrmann, and R. N. Poulsen, "RoboWeedSupport - Weed Mapping with drones using a DJI Phantom 4," 2016. (Online). Available: <https://www.youtube.com/watch?v=yegTo2mw6GA>. (Accessed: 07-Feb-2017).
- [10] J. Rasmussen, J. Nielsen, F. Garcia-Ruiz, and J. C. Streibig, "Potential uses of small unmanned aircraft systems (UAS) in weed research," *Weed Res.*, vol. 53(4), no. 242–248, pp. 242–248, 2013.
- [11] S. L. Madsen, M. S. Larsen, R. N. Poulsen, and R. N. Jørgensen, "RoboWeedSupport - Semi-automated UAS system for cost efficient high resolution in sub-millimeter scale acquisition of weed images," in *ECPA 2017 - 11th European Conference on Precision Agriculture*, 2017.
- [12] L. DJI Technology CO., "Creating a MapView and Waypoint Application," *DJI Mobile SDK Documentation*, 2016. (Online). Available: <https://developer.dji.com/mobile-sdk/documentation/ios-tutorials/GSDemo.html>. (Accessed: 07-Feb-2017).
- [13] M. Dyrmann, R. N. Jørgensen, and H. S. Midtiby, "RoboWeedSupport - Detection of Weed Locations in Leaf Occluded Cereal Crops using a Fully Convolutional Neural Network," in *ECPA 2017 - 11th European Conference on Precision Agriculture*, 2017.
- [14] M. S. Laursen, R. N. Jørgensen, M. Dyrmann, and R. N. Poulsen, "RoboWeedSupport - Sub millimeter weed image acquisition in cereal crops with speeds up till 50 km/h," in *ICPA 2017 - 19th International Conference on Precision Agriculture*, 2017.
- [15] L. DJI Technology CO., "Phantom 4 Pro Specs," 2017. (Online). Available: <https://www.dji.com/phantom-4-pro/info>. (Accessed: 07-Feb-2017).
- [16] P. Rydahl, N.-P. Jensen, M. Dyrmann, P. H. Nielsen, and R. N. Jørgensen, "RoboWeedSupport - Presentation of a cloud based system bridging the gap between in-field weed inspections and decision support systems," in *ECPA 2017 - 11th European Conference on Precision Agriculture*, 2017.
- [17] J. H. Jeppesen, R. H. Jacobsen, R. N. Jørgensen, R. Gislum, A. Halberg, and S. T. Toftegaard, "Improving Profitability in Precision Agriculture by Identification of High-Variation Fields based on Open Satellite Imagery," in *ECPA 2017 - 11th European Conference on Precision Agriculture*, 2017.
- [18] J. H. Jeppesen, R. H. Jacobsen, R. Nyholm Jørgensen, and T. S. Toftegaard, "Towards Data-Driven Precision Agriculture using Open Data and Open Source Software," in *International Conference on Agricultural Engineering 2016*, 2016.