Online adaptive path planning of UAVs for weed detection

Wolfgang Pitzl **Lukas Lachmann** **Raphael Völker**

Peter Riegler-Nurscher

Josephinum Research
Wieselburg, AT 3250
{wolfgang.pitzl, lukas.lachmann, raphael.voelker, p.riegler-nurscher }
@josephinum.at

Abstract

Problem weeds pose a challenge for agriculture. Robust detection of these plants is crucial for their control and for assessing possible contamination of the crop. Current UAV inspections are usually carried out using a fixed flight route, regardless of the extent of weed infestation. Initial approaches of adaptive flight control attempt to save flight distance by adapting flight altitude and route. We would also like to investigate adaptive gimbal guidance, to find out whether this can have a positive impact on flight paths and flight times. To this end, we developed a pipeline between the server including the operating website and the drone. The initial results, presented in this extended abstract, examine the functional capability of the pipeline and different error sources for GPS accuracy of adaptive gimbal pitches.

1 Introduction

Problem weeds such as thistles, which reproduce via underground rhizomes, and neophytes like the poisonous thorn apple pose challenges for agriculture. Reliable detection is essential for targeted control measures such as spot spraying and for assessing possible crop contamination.

Conventional UAV flights using lawn-mower coverage achieve high accuracy but cannot adapt to weed distribution. Regardless of weed density, the drone covers the entire field without evaluating or adjusting its flight path, and most commercial drones cannot perform evaluations during flight.

Adaptive approaches already attempt to adjust altitude and flight routes in real time and can achieve shorter flight paths (see: [1]–[5]). However, these studies do not consider variable gimbal positioning, as images are always taken in nadir view. This project investigates whether gimbal control can reduce flight path length and time without significantly affecting detection or localisation accuracy. As a first step, this extended abstract examines the functionality of our pipeline and potential GPS localisation errors at adaptive gimbal pitches.

2 Related Work

Previous research has explored online adaptive UAV flight paths for efficient mapping. The work of [1] used a predefined route with an OODA loop to recognize Aruco markers, red surfaces, and thistle plants. Paper [2] introduced an informative path planning strategy that maximizes information collection while respecting resource constraints, demonstrating higher efficiency than traditional

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approaches. In [3], adaptive flight height was used to reduce flight time while maintaining high segmentation accuracy. Similarly, [4] combined high-altitude coverage with low-altitude inspection paths, reducing flight lengths by 37% for clustered objects and 6% for uniformly distributed objects. The work in [5] applied deep Q-learning to learn search policies that outperformed baseline row-by-row flight paths and were transferable to real-world data. These studies indicate that online adaptive flights can shorten flight paths, but all rely on nadir images.

The work of [6] evaluated the accuracy of the Matrice 600 Pro with onboard GNSS RTK, producing photogrammetric products with decimeter accuracy. In contrast, our project uses drone footage captured from a standstill. For our application, accurate YAW indication is also important, yet existing research mainly focuses on RTK precision, as shown in studies [7] and [8].

3 Method

In this project, we evaluate GPS accuracy from drone images and compute adaptive routes on a server, with the aim of testing live processing over mobile networks in a later stage. This approach allows easy integration of different drones, as the drone only executes simple tasks provided by the server. Our goal is also to adapt this server-based pipeline for future research projects.

The system is based on a FastAPI application running on the server, providing API endpoints and web interfaces for control and monitoring. Through the control interface, the drone can be operated in three modes:

- Manual mode, where the user selects a target GPS position including altitude.
- Route mode, where predefined routes are uploaded and executed.
- Adaptive mode, where only a field shape file and an algorithm need to be selected.

The drone receives tasks from the server containing a GPS position, altitude, and an action. Possible actions include: (1) YAW rotation at the arrival point, (2) single-photo capture with wide-angle or zoom camera and selectable gimbal pitch, and (3) multi-photo capture with defined start and end points for gimbal pitch and YAW rotation.

Currently, we are developing the first adaptive algorithm, which:

1. Captures multi-photography (wide-angle) of the entire field or large sections of the field.
2. Evaluates suspected weed positions on the server using segmentation models and EXIF data while images are still being captured.
3. Generates zoom-camera single-photo tasks based on the detected GPS positions.

To assess the algorithm's accuracy, we examine potential error sources: (1) drone heading (YAW) accuracy, (2) GPS coordinates on the drone, and (3) the target object's position in the image. Experiments are conducted using a DJI Mavic 3T. While each factor will be tested repeatedly in the future to analyze variability, the current results are based on a single test per aspect.

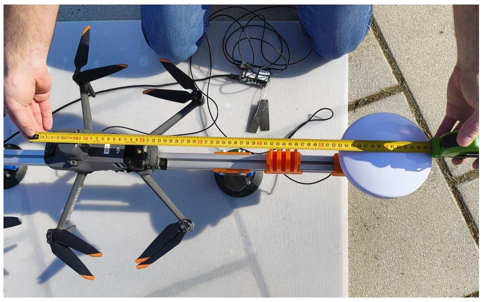
3.1 Heading (Yaw)-accuracy of the drone

We use a simpleRTK3B Pro to measure Heading with a central 116 cm aluminum profile and RTK-antennae at each end under the drone, and fixed the drone and gimbal to the aluminum profile (1a). We compare the heading from the simpleRTK3B Pro with gimbal-heading information from EXIF-data of UAV photos taken. As we cannot align the drone with perfect precision, we will get a constant offset for all measurements. This offset, estimated from the average misalignment will be removed from the measured difference. Overall we rotate the setup 360 degree and take 14 different measurements.

3.2 GPS-coordinate on the drone

From the previous heading (yaw)-accuracy test, we calculate the average distance from the simpleRTK3B-GPS-Position to the UAV-GPS-position (1b). We use this to estimate which GPS-Location on the drone is written into the EXIF-data.

(a) Heading (Yaw)-accuracy of the drone



(b) GPS-coordinate on the drone

Figure 1: Investigate potential error sources part 1

3.3 Impact of position of the target object in the image

A total of 13 markers were measured with an RTK antenna on a flat surface (6 × 10 m). From a central marker, three rows with four markers each extend in vertical, horizontal, and diagonal directions, ranging from markers 0 to 4 (2). The UAV was manually positioned so that the central marker appeared in the image centre and the outer markers near the edges. This results in a flight altitude of 14.34 m and a ground sample distance (GSD) of 5.2 mm/pixel for this setup, as a wide-angle camera with a focal length of 4.4 mm and a resolution of 4000 x 3000 pixels was used. The image was undistorted using OpenCV Camera Calibration. To compensate for RTK error in the UAV image, the calculated centre marker position was shifted to the ground-truth position, and all other marker positions were adjusted by the same offset. The calculated GPS coordinates were then compared with the RTK measurements.

Figure 2: Impact of image position

4 Results

4.1 Server-Drone-Pipeline

The visualization of the Server-Drone-Pipeline shows logged actions from an adaptive flight from the remote control. From 0 to 80 seconds the UAV performs a multi-photo at two different gimbal settings, the logs of yaw rotations are in the third row. At around 95 seconds, the drone switches the camera and performs 3 single-photos, each time rotating gimbal and yaw.

4.2 Heading (Yaw)-accuracy of the drone

10 of 14 Measurements are in the standard deviation of the simpleRTK3B. We conclude from this data that the UAV heading doesn't have a high noise and the accuracy is ±0.4 degree. We were unable to find any reasons in other EXIF parameters as to why the values 3,4 and 12 are noticeably outside the standard deviation. Therefore, we will repeat this test during the course of our project to make reliable conclusions and try to find out why some values are outside the standard deviation.

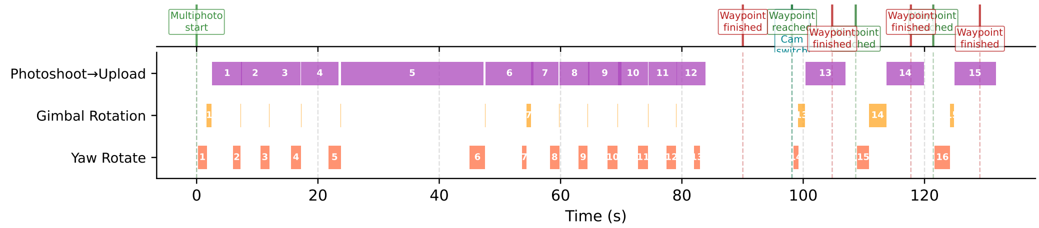


Figure 3: Visualization of pipeline from the UAV remote control

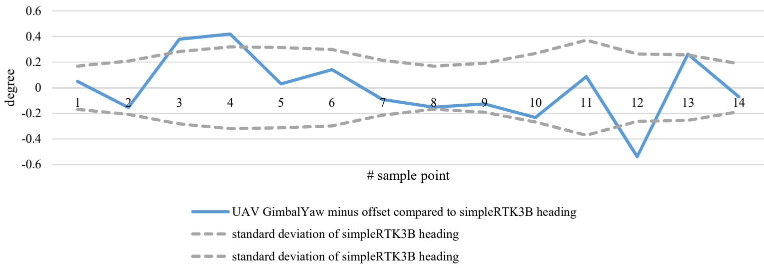
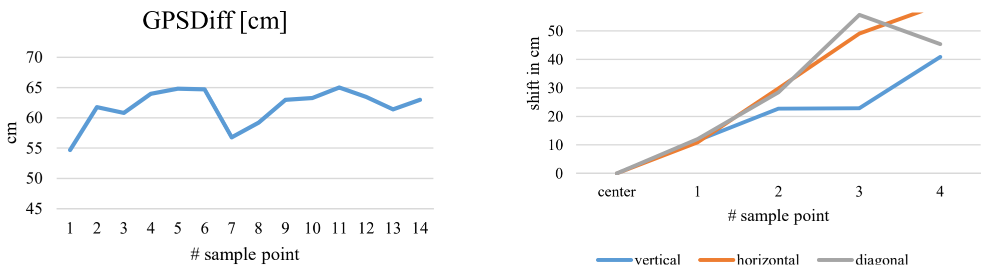


Figure 4: Heading (Yaw)-accuracy of the drone

4.3 GPS-coordinate on the drone

The average distance from the simpleRTK3B-GPS-Position to the GPS-Position give of the drone is 61,84cm and ranges from 54,7cm to 64,8cm (5a). Figure fig:distance shows that the distance from the centre of the white RTK antenna to the drone's gimbal is approximately 61 cm. We conclude from this data, that the GPS-Position given by the drone is the GPS-Position of the gimbal. However, as the scattering of the distance is relatively high, we will repeat this test several times.



(a) GPS-coordinate on the drone (b) Impact of position of the target object in the image

Figure 5: Diagrams of potential error sources part 2

4.4 Impact of position of the target object in the image

The graph (5b) is showing, that for most of the marker points its true, that the further away a marker is from the center (marker 0) the higher is the shift between the calculated GPS from the image to the measured GPS-coordinate.

5 Discussion

The presented server–drone pipeline appears promising, and future work will evaluate it in different scenarios for weed detection and compare flight path length and time with conventional lawn-mower coverage flights. Apart from weed detection, we could envisage using this drone-server pipeline to monitor field robots. Or even for gesture control, where very specific and custom drone actions for different gestures are stored on the server.

The yaw accuracy of the drone was tested only on the ground, as evaluating it during flight is technically challenging. This limitation reduces the validity of the results. Following the initial test of yaw accuracy, we are not yet able to explain why some values fall outside the standard deviation. We hope to gain further insights through further repetitions and by calibrating the compass using the DJI Pilot 2 app.

We also really want to find out why the shift increases as the distance from the centre point (5b) increases. We suspect this may be due to incorrect photo-correction parameters or minor errors in calculating the GPS positions. We need to examine our approach in more detail.

Following this initial round of testing, we are still cautious about making any definitive statements. As mentioned earlier, the tests for the different error sources will be repeated multiple times to obtain more reliable results.

In addition, the ongoing project will investigate the influence of different gimbal pitches on GPS localisation accuracy. We suspect that the higher the gimbal pitches (i.e. the further the drone looks away), the greater the error in calculating GPS positions. Perhaps high gimbal pitches always produce positions that are too imprecise for spot spraying. It would be important to know this to limit the adaptive gimbal pitch to a specific range.

References

[1] Alsalam, B. H. Y., Morton, K., Campbell, D., & Gonzalez, F. (2017, March). Autonomous UAV with vision based on-board decision making for remote sensing and precision agriculture. In 2017 IEEE Aerospace Conference (pp. 1-12). IEEE.

[2] Popović, M., Vidal-Calleja, T., Hitz, G., Chung, J. J., Sa, I., Siegwart, R., & Nieto, J. (2020). An informative path planning framework for UAV-based terrain monitoring. Autonomous Robots, 44(6), 889-911.

[3] Stache, F., Westheider, J., Magistri, F., Stachniss, C., & Popović, M. (2023). Adaptive path planning for UAVs for multi-resolution semantic segmentation. Robotics and Autonomous Systems, 159, 104288.

[4] van Essen, R., van Henten, E., Kooistra, L., & Kootstra, G. (2025). Adaptive path planning for efficient object search by UAVs in agricultural fields. Smart Agricultural Technology, 12, 101075.

[5] van Essen, R., van Henten, E., & Kootstra, G. (2025). UAV-based path planning for efficient localization of non-uniformly distributed weeds using prior knowledge: A reinforcement-learning approach. Computers and Electronics in Agriculture, 237, 110651.

[6] Ekaso, D., Nex, F., & Kerle, N. (2020). Accuracy assessment of real-time kinematics (RTK) measurements on unmanned aerial vehicles (UAV) for direct geo-referencing. Geo-spatial information science, 23(2), 165-181.

[7] Czyża, S., Szuniewicz, K., Kowalczyk, K., Dumalski, A., Ogrodniczak, M., & Zieleniewicz, Ł. (2023). Assessment of accuracy in unmanned aerial vehicle (uav) pose estimation with the real-time kinematic (rtk) method on the example of dji matrice 300 rtk. Sensors, 23(4), 2092.

[8] Lewicka, O., Specht, M., & Specht, C. (2022). Assessment of the Steering Precision of a UAV along the Flight Profiles Using a GNSS RTK Receiver. Remote Sensing, 14(23), 6127.