

# UAS LIDAR LOCAL MAXIMUM FILTERING FOR INDIVIDUAL MAIZE DETECTION

Jordan Steven Bates<sup>1\*</sup>, François Jonard<sup>1,2</sup>, Harry Vereecken<sup>1</sup>, Carsten Montzka<sup>1</sup>

1. Institute of Bio- and Geosciences: Agrosphere (IBG-3), Forschungszentrum Jülich GmbH, 52428 Jülich, Germany
2. Earth Observation and Ecosystem Modelling Laboratory, SPHERES Research Unit, Université de Liège (ULiège), Allée du Six Août 19, 4000 Liège, Belgium

## ABSTRACT

As unmanned aircraft systems (UAS) remote sensing technology has advanced, providing unprecedented resolution, crop status at the individual plant level has become popular. Often plant detection is performed using high resolution RGB cameras that utilize algorithms and machine learning methods centered around trained pixel patterns of object textures. Similar methods with UAS LiDAR are not as explored considering their more recent UAS adaptation and the significantly larger price tag. Methods that have been created center around individual tree detection using crown delineations utilizing the height information and local maximum filtering. This study explores if this methodology can be used in a similar way for crops such as maize.

**Index Terms**— Crop detection, UAS, LiDAR, Machine Learning

## 1. INTRODUCTION

Precision farming has rapidly been adapting unmanned aircraft systems (UAS) remote sensing methods as sensors, platforms, and software have advanced and become more practical and accessible [1]. With the ability to fly close to the ground with high-resolution cameras, UAV remote sensing allows for more detailed information about the plant structure and surrounding textures such the bare soil to be better represented. Common methods of crop detection using passive sensors include thresholding and machine learning methods such as deep convolutional neural networks (CNN) [3].

Individual crop detection utilizing UAS LiDAR has yet to be seen. This is mainly due to the very recent UAS adaptation with the decreased size and weight of LiDAR sensors [2]. Additionally, LiDAR is still more expensive than their passive counterparts and requires more expert knowledge to process the data. However, LiDAR's depth information tends to provide better plant characterization as the signal of this active sensor is able to penetrate through gaps in the vegetation allowing for more information within and under

the canopy [4]. Studies have used this advantage to discover canopy densities that can be related to LAI [5] or measure tree trunk diameters in forestry [6]. This ability to provide structural information throughout the vertical extent of the vegetation, rather than just top surface textures, opens alternative avenues for individual crop detection.

LiDAR individual detection concerning the environment has only been applied in forestry applications [1]. The most used method of individual tree detection using airborne LiDAR is with the local maximum filtering (LMF) algorithm [1]. This study attempts to apply the LMF methods to maize to assess the potential of these methods within crop monitoring.

## 2. METHODS

### 2.1. Study Area

The study was conducted at the PhenoRob Central Experiment at Campus Klein-Altendorf (CKA) in Germany. The flight was conducted on July 20<sup>th</sup> near the middle of the growth stages of maize. The maize experiment area was segmented from the rest of the CKA point cloud for the analysis performed.



Figure 1. (a) Aerial overhead nadir image of the maize plot used for the study. (b) Ground image of the side profile of the maize crops of interest.

### 2.2 Equipment

A YellowScan Surveyor LiDAR was used onboard a DJI Matrice 600 pro hexicopter UAS. The LiDAR is composed of a Velodyne LiDAR puck for sending and receiving the

light signal, inertial measuring units (IMU) for sensor orientation, global navigation satellite system (GPS) for sensor locations, and an onboard computer where the sensor information is combined and synchronized. A Septentrio NR3 GNSS was used as a base station to provide the needed data of PPK georeferencing of the scanned scene. The UAS was flown in a cross hatch flight profile with scan overlaps of 50% at scan angles of 18%. The flight altitude was 50 meters above ground level and the speed was 5 m/s.

### 2.3 Data Processing

YellowScan's CloudStation software specific to their LiDAR systems was used to produce the 3D point cloud from the puck recording where each flight scan is registered with one another. During this process the data point cloud is also georeferenced using a precise point positioning solution (PPP) from a smooth best estimated trajectory file (SBET) created with the UAS LiDAR trajectory files and Applanix's POSpac software [6].

After preprocessing, the ground was classified and segmented using the cloth simulation filter (CSF) method [7]. This is needed in order to normalize the height of the point cloud by creating a raster of the ground heights, referred to as a digital terrain mode (DTM). The DTM was subtracted from the point cloud heights.

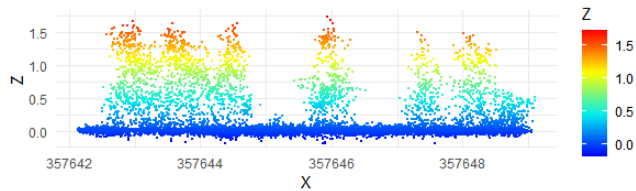


Figure 2. Height side profile of a segmented section of the 3D point cloud within the scanned maize location. This serves to show how the width and leaf density of each maize crop is greater around its base and mid-section while becoming narrower toward the top.

Once the heights are known, the minimum and maximum heights to be considered can be adjusted by adjusting the points of interest. The LMF filter was then employed using an R package, lidR. A smoothing window size parametrization was changed and chosen based on what produced the best results.

Assessment of the detection performance was done using the method used in the study with Mohan et al. 2021. The formulas used can be seen below (1)-(3). These results include recall ( $r$ ) with true positive (TP) and false positive (FP), precision ( $p$ ) using TP and false positive (FP), and F-score (F) [1].

$$r = TP / (TP + FN) \quad (1)$$

$$p = TP / (TP + FP) \quad (2)$$

$$F = 2 * r * p / (r + p) \quad (3)$$

### 3. RESULTS & DISCUSSION

The detection results can be visualized in a 3D environment with the detections represented by 3D spheres above the 3D point clouds of the crops as seen in Figure 3.

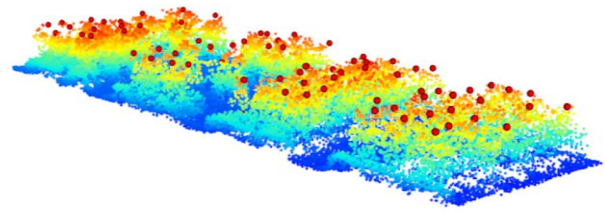


Figure 3. 3D view of the maize plot area with the red 3D spheres on the top identifying each individual maize crop.

The resulting performance of the LMF method used was a F-score of approximately 0.7. The results of the LMF method used resulted in good accuracy although it might be considered slightly lower than with other studies in forestry [1]. It could be possible to improve the results with the collection parameters used. With lower flight altitudes, slower speeds, higher overlap, or a different scan angle could increase the point density, detail, and overall plant characterization.

With the ability to count the individual crops, yield estimation can automatically be derived [8]. Knowing how many seeds were planted beforehand, the emergence rate can be computed [8]. Emergence uniformity can also be monitored considering that the spatial density of the plant detection can be inspected. Knowing the count and location of each plant, stresses and diseases affecting the field can be assessed more precisely.

### 4. CONCLUSION

This study proves there is potential in using LMF methods, commonly used in forestry, with UAS LIDAR to detect individual crops such as maize. Theoretically, it is possible to improve the results with improved data collection parameters. Whether this can also be applied to other crops or other collection methods, such as structure from motion (SfM), still needs to be researched. However, the results thus far have proven to be comparable to other studies in forestry.

## ACKNOWLEDGEMENTS

Research partially funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy-EXC 2070 –390732324.

## REFERENCES

- [1] Mohan, M., Leite, R. V., Broadbent, E. N., Jaafar, W. S. W. M., Srinivasan, S., Bajaj, S., Corte, A. P. D., Amaral, C. H. do, Gopan, G., Saad, S. N. M., Kamarulzaman, A. M. M., Prata, G. A., Llewelyn, E., Johnson, D. J., Doaemo, W., Bohlman, S., Zambrano, A. M. A., & Cardil, A. (2021). Individual tree detection using UAV-lidar and UAV-SfM data: A tutorial for beginners. *Open Geosciences*, 13(1), 1028–1039.
- [2] ten Harkel, J., Bartholomeus, H., & Kooistra, L. (2020). Biomass and Crop Height Estimation of Different Crops Using UAV-Based Lidar. *Remote Sensing*, 12(1), 17.
- [3] Valente, J., Sari, B., Kooistra, L., Kramer, H., & Mùcher, S. (2020). Automated crop plant counting from very high-resolution aerial imagery. *Precision Agriculture*, 21(6), 1366–1384.
- [4] Wang, T., Liu, Y., Wang, M., Fan, Q., Tian, H., Qiao, X., & Li, Y. (2021). Applications of UAS in Crop Biomass Monitoring: A Review. *Frontiers in Plant Science*, 12, 616689.
- [5] Neuville, R., Bates, J. S., & Jonard, F. (2021). Estimating Forest Structure from UAV-Mounted LiDAR Point Cloud Using Machine Learning. *Remote Sensing*, 13(3), 352.
- [6] Bates, J. S., Montzka, C., Schmidt, M., & Jonard, F. (2021). Estimating Canopy Density Parameters Time-Series for Winter Wheat Using UAS Mounted LiDAR. *Remote Sensing*, 13(4), 710.
- [7] Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., & Yan, G. (2016). An Easy-to-Use Airborne LiDAR Data Filtering Method Based on Cloth Simulation. *Remote Sensing*, 8(6), 501.
- [8] Valente, J., Sari, B., Kooistra, L., Kramer, H., & Mùcher, S. (2020). Automated crop plant counting from very high-resolution aerial imagery. *Precision Agriculture*, 21(6), 1366–1384.