On Crop Height Estimation with UAVs

David Anthony, Sebastian Elbaum, Aaron Lorenz, and Carrick Detweiler

***Abstract*— Remote sensing by Unmanned Aerial Vehicles (UAVs) is changing the way agriculture operates by increasing the spatial-temporal resolution of data collection. Micro-UAVs have the potential to further improve and enrich the data collected by operating close to the crops, enabling the collection of higher spatio-temporal resolution data. In this paper, we present a UAV-mounted measurement system that utilizes a laser scanner to compute crop heights, a critical indicator of crop health. The system filters, transforms, and analyzes the cluttered range data in real-time to determine the distance to the ground and to the top of the crops. We assess the system in an indoor testbed and in a corn field. Our findings indicate that despite the dense canopy and highly variable sensor readings, we can precisely fly over crops and measure its height to within 5cm of measurements gathered using current measurement technology.**

Fig. 1. Micro-UAV measuring crop height

I. Introduction

UAVs are improving modern agriculture production and research by providing data at higher temporal and spatial resolution scales, and lower cost, than traditional collection methods, such as manned aircraft and satellites [1], [2]. Micro-UAVs offer further potential benefits as they lower costs and operator risks, accelerate deployment times, and are able to operate closer to crops to increase spatial resolution. Operating close to the crops also allow UAVs to utilize new sensors, such as low power, passive devices, that are not effective with high flying aircraft.

In this work, we develop a crop height measurement system based on a micro-UAV platform, shown in Figure 1. Obtaining accurate and timely crop height estimates is important to characterize plants' growth rate and health. Agricultural researchers use this data to measure the impact of genetic variation in the crops on drought resistance and responses to environmental stresses. Practitioners may also use crop height information to assess crop development and plan treatments [3]. These measurements are currently obtained through manual measurement, or by driving heavy equipment through the field. These collection methods are time consuming and damaging to the crops, and as such, are not regularly used [4], [5], [6].

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Measuring crops requires height estimates of the tops of the crop and the ground, the difference of which is the crop height. Measuring crops from the air to characterize the top of the canopy benefits from unobstructed movement that does not damage the crops, but locating the ground is more challenging as layers of plants' leaves can obscure the ground. There are two ways to overcome this challenge. One way is to increase sensing power by using, for example, radars or powerful LiDARs. An alternative approach, the one we have chosen to reduce risk and cost, is to fly a micro-UAV equipped with less powerful sensors but operating closer to the crops to exploit small gaps in the crop canopy to directly sense the ground and the lower levels of the vegetation.

The autonomous crop height measurement system presented in this work is being developed in conjunction with agronomy researchers with the goal of computing corn crop height within 5cm of manual measurements, while increasing the areas and frequency of measures by two orders of magnitude. The system utilizes low-cost sensors and a UAV platform to reduce costs and operator risks, increase operating ease, and be highly portable. The system is built using a commercial micro-UAV, laser scanner, barometer, IMU, and a GPS receiver to effectively operate the UAV over crops, estimate the UAV altitude, and accurately measure the crop's height by applying a series of onboard filters and transformations. By operating at a low altitude, the system greatly increases the spatial resolution of the collected data, when compared to traditional approaches. Furthermore, the small size and weight of the system limits the risks of operating the unit.

The contributions of this work are:

- Design and implementation of a micro-UAV mounted crop measurement system. The system leverages a downward mounted laser scanner to help maintain the

UAV close to the crops and to characterize the crops profile. This profile is then processed through a series of transformations and filters to compute the UAV's altitude and the crop's height.

- Assessment of the system on an indoor testbed and a field. Our findings show that the system has the potential to significantly increase the data obtained versus current mechanisms and still operate within the margin of error acceptable by agricultural scientists,

II. Background

Before discussing the details of our work, we review related work in using UAVs in agriculture and related fields.

A. UAVs in Agriculture

The use of UAVs in agriculture is an active research topic [7]. Existing work mostly utilizes UAVs to deliver aerial imagery of fields in a more timely and lower cost manner than traditional methods, such as manned aircraft and satellite imagery. Using a large UAV, it is possible to classify different vegetation in a field [8]. Differentiating between vegetation types is used for weed management practices and coordinating ground robots [9]. Small rotorcrafts operating at altitudes of 200m above the ground and speeds of 30km/h are capable of surveying up to 70ha/hr [1]. A smaller UAV operating at ranges of 10m above the ground is capable of surveying rice paddies with a multi-spectral camera [10]. By operating close to the crops, the impact of atmospheric distortion is reduced, but fast and accurate altitude measurements are needed.

In our approach, we fly even closer (within 1-2m) to the crops. This low-altitude operation increases the spatial resolution of the collected information beyond the limits of traditional aerial imagery techniques. Flying close to the crops allows the UAV to exploit gaps in the crops' foliage to detect the ground and sense the multiple layers of leaves.

B. Tree Canopy Estimation

In forestry applications there has been a significant amount of research using 3D LiDARs to measure canopy cover, biomass, and tree heights. Tree heights have been assessed using man-portable LiDAR systems [11], collecting data similar to what we desire to collect for corn crops. This system is cumbersome as it requires scientists to reposition the system at all data collection points. Our use of micro-UAVs significantly reduces the time needed to conduct an experiment because the UAV can quickly survey a field without requiring a human to relocate bulky equipment.

LiDARs have been used in conjunction with aerial platforms for forestry experiments as well. LiDARs generally require larger platforms that are difficult and risky to operate close to crops, which means they are forced to fly at high altitudes where the irregularity of the tree shapes makes feature extraction difficult [12]. These conditions also push LiDARs outside their recommended operating specifications. UAVs can mitigate these problems [13] by flying at altitudes between 10-40m, which produces information with a higher spatial density. At these altitudes, a heavy and expensive LiDAR is needed to achieve a high spatial information density.

Existing work differs from our approach, in that we are using a laser scanner (2D scan) instead of a LiDAR (3D image) due to payload limits of micro UAVs. Furthermore, we are interested in aggregate information about heights of groups of plants, not individual plants, We also must fly much closer to the crops to sense the ground between the plants, which requires more precise altitude control than these forestry approaches. Finally, the use of small laser scanners reduces the size and cost of the combined system, which makes it safer to use for operators.

C. SLAM

Simultaneous localization and mapping (SLAM) algorithms have been an area of intense research. SLAM algorithms using only a laser scanner in an urban environment [14] are accurate for ground vehicle navigation. Outdoor SLAM has been accomplished using a combination of vision and laser ranging data [15], which can increase the accuracy, at the cost of computational complexity. Actuated planar laser scanners have been shown to work in unstructured environments such as forests [16], but require extremely intensive computation, and are not suitable for real time navigation for aerial robots requiring precise height control.

SLAM approaches are ill-suited for our work, as we do not seek to create a detailed map of the entire environment, but only to extract group statistics, such as crop height from fields. Furthermore, SLAM approaches do not work well with the dynamic and complex field environment (e.g., plants move with the wind, leaves appear different under changing light conditions), making it more difficult to sense with high enough precision to extract persistent features from sensor data. Finally, the computing power necessary to make real time navigation close to the crops is not viable in the micro-UAVs. Instead, we rely on GPS to localize the UAV in the field.

Fig. 2. Corn plant measurement

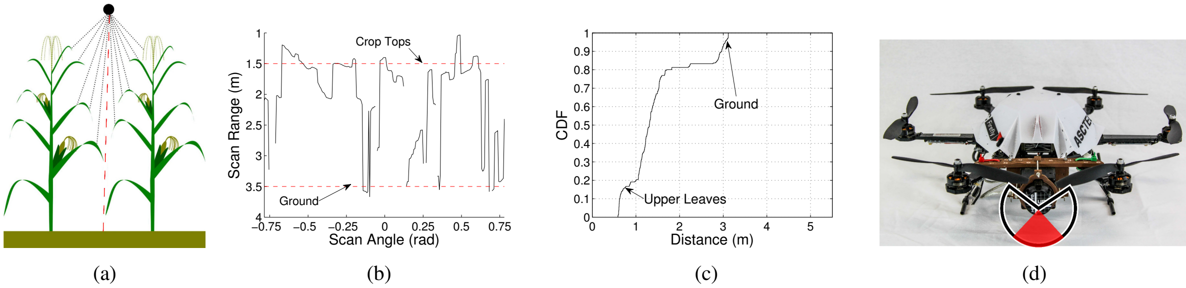


Fig. 3. (a) Illustration of UAV measuring corn (b) sensor readings from corn field (c) distribution of sensor data (d) UAV with laserscanner with 90° scan angle in red

D. Corn Plant Structure and Measurement

Surveying agricultural fields requires an understanding of the underlying vegetation. In this paper, we restrict our studies to corn fields, but we discuss the generalization to other types of crops in Section VI. A typical mature corn plant has 12-22 leaves arranged along the stalk that grows to a height of 2-3m [17]. The point at which a leaf joins the stalk is referred to as a 'node.' As the plant matures, a thin, long, tassel emerges from the top of the plant.

The structure of a corn plant makes it challenging to survey fields, not only from the air, but also manually from the ground. The corn is typically planted in rows that are spaced 30 or 36 inches ($76.2/91.44$cm) apart. As the corn grows, the leaves form a dense canopy between the rows, which limits an aerial vehicle's view of the ground. Typically, the height of the plant is defined as the distance from the top node to the ground. Figure 2 shows the standard method of manually measuring the height of corn in a field. This hand measurement process is labor intensive and error prone. Tractors with specialized measuring devices can measure the crops in a field, but will damage both the plants and the ground [18]. Thus, it is only infrequently performed on a small subset of plants in a field, despite the large impact such measurements could have on crop production.

III. UAV Altitude and Crop Height Estimation

We now present our measurement system that addresses the difficulties of using a micro-UAV to survey crops, namely locating the tops of the crops, and the ground.

A. Locating the top of the crops and the ground

Estimating crop height with an accuracy of 5cm requires estimates of similar accuracy for the location of the ground and the plants' tops to compute their differential. [1]

Determining the ground and crop top location, however, can be challenging. The foliage of the corn fields makes it difficult to directly sense the true ground location. An illustration of the problem is shown in Figure 3(a). In this figure, the UAV is attempting to sense the ground using multiple sensor readings, represented by the dashed lines. The layers of leaves block most of the sensor measurements, represented by the dotted black lines. Only one sensor measurement, shown in the red dashed line, finds a narrow gap in the foliage to reach the ground. Similarly, without enough readings the top of the crop may be missed. From these readings, statistics such as the crop height can be computed, and by georeferencing the scans with GPS, height maps of the field can be constructed.

In practice, the measurements also include noise. Figure 3(b) shows a single laser scan obtained at a corn field. The x-axis represents the sample angle in reference to the UAV's body. The y-axis represents the distance from the scanner to a surface. As expected, there is some height variation across the top of the plants, at some angles the values are invalid (not plotted), and the corn leaves block most of the scans at the upper layers of leaves. However, the single scan reveals that some readings have reached the ground which in the figure is consistently located at ≈ 3.5m from the UAV. Clearly, more scans and readings per scan increase the probability of sensing through the canopy and better characterizing the crop's top.

We now use the empirical cumulative distributed function (CDF) of the scan in Figure 3(b) to get a better sense of how to interpret it. The distribution in Figure 3(c) makes it easier to identify the different elements of the crop. The upper layer of leaves is represented by the sudden jump at the 0.5m mark in the CDF. The multiple layers of leaves then smooths the distribution until the 1.75m mark. At this point, the plants are largely leaf free, so most scans then reach the ground at around the 3.5m mark. This profile of CDF is characteristic of the crop scans obtained from the micro-UAV operating close to corn crops, and it hints at the potential of extracting plants' tops and ground estimates from it.

We formalize this problem by representing the scans as a multinomial distribution. The ranges reported by the sensor are discretized into a set of k ranges, h_k. The leaves' density determines the probability p_k of the sensor detecting one of the leaves at height k. The number of readings reported in each location is the set of n trials for the multinomial distribution. We seek to find two percentiles, p_g and p_c, which can be used to estimate the ground and crop top location from the distribution of the laser scans.

Characterizing the plants in this way places certain requirements on the sensor being used to gather the readings. First, it must be able to quickly collect many samples from a

[1] As we shall see in Section III-C, accurate ground measures are also valuable to maintain a UAV altitude within a band that is safe but still close enough to the crops to collect the required data.

1: $estimated\_crop\_height \leftarrow 0$
2: $num\_scans \leftarrow 0$
3: **procedure** ESTIMATECROPHEIGHT(p_g, p_c)
4: **while** PendingWaypoints **do**
5: $[L] \leftarrow Scanner()$ ▷ Get data from scanner
6: $(r, p, y) \leftarrow IMU()$ ▷ Get data from IMU
7: $b \leftarrow Barometer()$ ▷ Get barometric altitude estimate
8: $(altitude, scan\_crop\_height) \leftarrow ProcessScan([L], r, p, y, b, p_g, p_c)$
9: $UAVControl(altitude)$ ▷ Control the UAV altitude
10: $estimated\_crop\_height \leftarrow estimated\_crop\_height + scan\_crop\_height$
11: $num\_scans \leftarrow num\_scans + 1$
12: **end while**
13: **return** $estimated\_crop\_height/num\_scans$ ▷ Return the estimate crop height for the field
14: **end procedure**
15:
16: **procedure** PROCESSSCAN($[L], r, p, y, barometer, p_g, p_c$) ▷ Crop and UAV Height Estimation from laser scans [L],
17: ▷ the roll, pitch, and yaw of the UAV, the barometric pressure derived UAV height estimate,
18: ▷ and the parameters for estimate the location of the ground and the top of the crop
19: $F \leftarrow ConeFilter([L])$ ▷ Only keep center 90° of scans
20: $Z \leftarrow F * EulerRotation(r, p, y)$ ▷ Transform from UAV frame to world frame
21: $P \leftarrow Percentile(Z)$ ▷ Assign a percentile rank $p \in P$ to every range $z \in Z$
22: $\{g, h\} \leftarrow Estimator(P, Z, p_g, p_c)$ ▷ Ground and top of crop corresponds to specific percentiles in Z
23: $filtered\_g \leftarrow MedianFilter(g)$ ▷ Pass ground estimate through median filter, length w
24: $filtered\_h \leftarrow MedianFilter(h)$ ▷ Pass crop top estimate through median filter, length w
25: $scan\_crop\_height \leftarrow filtered\_g - filtered\_h$ ▷ Estimate the height of the crop in the scan
26: $altitude = Kalman(filtered\_h, barometer)$ ▷ Estimate UAV's height based on barometer and laser
27: **return** $\{altitude, scan\_crop\_height\}$ ▷ Return the two values estimated by the procedure
28: **end procedure**

Algorithm 1: Crop height and altitude estimation system

given area, so that the probability distribution is meaningful. Second, it must have a narrow sensing radius, so that the measurements can pass through the small gaps in the leaves, and thus sense the ground.

B. Platform

Figure 1 shows our complete system operating over crops. It is based on an Ascending Technologies Firefly hexacopter [19] which has a maximum payload of 600g, of which we use 528g. We augmented the UAV with a Hokuyo URG-04LX-UG01 laser scanner, which is mounted in a downward facing configuration under the UAV, as shown in Figure 3(d). The laser scanner produces a 240° scan at 10Hz, with an angular resolution of $\approx\ 0.36^\circ$, which creates 683 range readings per scan. The scanner has a maximum range of 5.6m. The scanner has an integrated filter which indicates which ranges are invalid. While the scanner is intended for indoor sensing, our tests in Section V show that when mounted in a downward facing configuration without a direct view of the sun, it will function effectively in an outdoor environment. An onboard Atomboard processor interfaces to and processes data from the laser scanner. The onboard GPS and IMU are used in conjunction with the laser scanner to control the UAV height. The software on the Atomboard is developed in ROS [20], and its functionality is described in the next section.

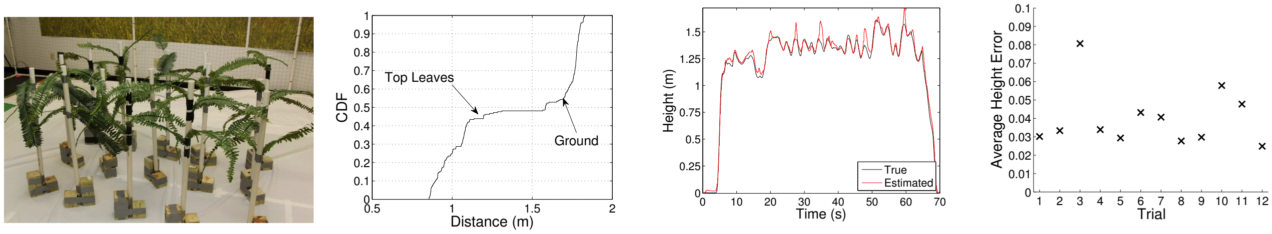
We assume that the crops are no more than three meters tall. By flying the UAV within one meter of the plants' tops, the spatial resolution of the laser scans enables stable height control and accurate estimates of crop height, as we will see in the following sections.

C. Crop Height and UAV Altitude Estimation

Converting the laser scan information into a crop height and UAV altitude estimate is a multi-step procedure, as outlined in Algorithm 1. The measurements from the laser scanner must be converted to altitude estimates, filtered, and transformed to extract estimates of the crop height and UAV altitude. Algorithm 1 presents the high level algorithm for this procedure. Procedure *EstimateCropHeight* collects sensor readings from the onboard sensors and uses the measurements to process each laser scan, using Procedure *ProcessScan*. *ProcessScan* returns an estimate of the UAV altitude and the height of the crop in the scan. *EstimateCropHeight* uses the two estimates to control the UAV, and estimate the height of the crops in the area of interest. Next, we describe the operation of *ProcessScan* in detail.

Cone Filter: The *ConeFilter* procedure on line 19 of Algorithm 1 decimates each laser scan reading, leaving a 90° arc of samples that are within 45° of the z-axis of the UAV. The full 240° scan range is shown as a black and white arc in Figure 3(d), and the used samples are from the region shown in red. Rejecting all of the scan information from outside this region eliminates the readings from the UAV's body, samples where the ground is outside the maximum range of the scanner, and other readings that do not sense the crop. Since the UAV does not aggressively maneuver during a surveying mission, filtering early significantly cuts the computational burden of later stages without losing useful information.

The cone filter, combined with the maximum range of the laser scanner produce an upper limit to the UAV's altitude. Given the difficulties in sensing the ground, all of the scans in the 90° need to have a chance of reaching the ground, in



(a) (b) (c) (d)

Fig. 4. (a) Indoor testbed (b) CDF of indoor scan data (c) autonomous flight height (d) average estimated altitude error

order to maximize the probability of detecting the ground. Since the laser scanner has a maximum range of 5.6m, this restricts the UAV to an altitude of $5.6 * \cos(45°) = 4.0$m.

Frame Transformation: Next, the remaining range data is transformed from the body frame of the UAV, to the world frame. On line 20 of Algorithm 1, roll, pitch, and yaw data from the onboard IMU is used in a standard Euler rotation matrix to extract the z-components of the range data in the global frame, and to compensate for the pitch and roll of the UAV.

Percentile Computation & Range Estimation: The percentile rank of each z-component is then computed (line 21 of Algorithm 1). Since we assume that the ground and top of the crop will be parameterized at a certain percentile of the data, the percentile ranks are used to estimate where the ground and crop is in each scan. On line 22, the *Estimator* procedure uses the percentile ranks and z-components to extract estimates of the UAV height and distance to the crops for each scan. The *Estimator* procedure searches through the percentile ranks, P, to find the closest percentiles to the ground and crop top estimates, p_g and p_c. The distances in Z that correspond to these percentiles are then returned as the ground and crop top distance estimates.

p_g and p_c are user defined parameters that must be experimentally derived. In the following sections, we show that it is not difficult to find pairs of these parameters that enable accurate altitude and crop height estimates.

Median Filtering: The crop top and ground range estimates are noisy, and tend to have outliers. The outliers are caused by infrequent scans where no range measurements reached the ground, abnormal plant growths, and occasional debris in the field. Each estimate of the ground and crop top is passed through a median filter, of length w, on lines 23 and 24 of Algorithm 1. The filter length is empirically determined. If it is set to a shorter length, the system is vulnerable to outliers. A longer filter length rejects more outliers, however, filter length introduces time lag in the control system, and the UAV becomes less responsive to altitude changes.

Flight Control: The filtered estimate of the ground distance is used in the flight control software. The laser scanner derived height estimate is combined with the barometric pressure height estimate, using a Kalman filter (line 26 of Alg. 1). The Kalman filter produces the final height estimate that is used by a PID control system to guide the UAV.

Crop Height Estimate: The crop height estimate for each scan is estimated by taking the difference between the estimated distance to the top of the crop, and the filtered distance to the ground. The crop height estimates for an area of interest are accumulated during the flight, and by averaging the crop height estimate from several of these scans, the crop height in an area can be estimated.

IV. Assessing Autonomous Altitude Control over Cluttered Ground

Before characterizing the system's ability to measure crop height in a field, we evaluate the accuracy of the system's altitude control described in the previous section in an indoor environment. The testbed contains artificial plants with multiple levels of long, narrow leaves to simulate corn plants. The plants are placed in 12 different configurations of rows spaced 0.5m apart. The configurations differ in the plant arrangements to ensure the results are not dependent on a particular ordering of plants. There are also two kinds of configurations of different density. In configurations 1-10 the plants are spaced between 40 and 50cm apart. Configurations 11-12 are denser, with plants placed 20cm apart within a row, and are meant to assess the system's ability to operate over extremely dense foliage, where fewer laser measurements reach the ground. The artificial plants have a mean height of 0.967m and a standard deviation of 3.74cm. The indoor testbed is shown in Figure 4(a). We used a Vicon motion capture system to provide ground truth estimates of the true UAV height [21].

For the evaluation we selected the 95^{th} percentile of the longest range reported by its scanner (p_g in Algorithm 1), with a median filter of length 3 (w in Algorithm 1) applied to the altitude estimate to reduce noise. These values are empirically determined from experimentation. The UAV maintains a stable altitude with the filter length, and quickly reacts to any perturbations. From Figure 4(b), we can see that the system should not be sensitive to the exact choice of p_g, and our results confirm this intuition.

Figure 4(c) shows the ground truth altitude of the UAV versus the pose calculated using our system estimate for one trial. The estimated altitude follows the true height extremely closely, and the UAV transitioned between the areas covered by the plants, and bare floor with few significant changes in altitude estimates. There are four instances where the altitude estimate has a minor divergence from the ground truth estimate, but the system quickly recovers. Increasing the filter length w would mitigate these problems, but could make the system less responsive to true changes in height, and thus more difficult to control.

Figure 4(d) shows the average difference between the true height and our system estimated altitude for all twelve configurations. The system has an average error of 4.1cm for the first ten sparse configurations, and an error of 3.6cm for the final two dense configurations. The variance for all configurations was 0.0003. This small error confirms that the system is consistently tracking the true ground, and the choice of p_g is valid.

Our indoor evaluation indicates that the system is able to accurately estimate and control its true altitude, even when it is flying over cluttered ground. Since the system is able to control its true altitude, it is able to consistently detect the ground. We will use the parameterization of p_g and w from this section to estimate the crop's height in the next section.

V. Experimental Height Estimation Results

We now evaluate whether the system is able to accurately measure a crop's height. The results of the prior section demonstrate that the system can sense the ground through severe clutter. If the system is able to reliably track the top of the plants, it will therefore be able to estimate the crop height, by taking the difference between the ground estimate and the crop top distance estimate. The system is evaluated using both the indoor testbed introduced in the prior section, and the outdoor field shown in Figure 1.

A. Outdoor Testbed

An outdoor testbed is needed to assess the system's ability to measure a real crop, and to test the laser scanner's effectiveness outdoor. Initial tests revealed that the scanner will not function when placed with a direct view of the sun. However, by mounting the scanner in a downward facing configuration, the 96.5% of the range measurements in each scan were valid, on average.

To create the ground truth estimate for the outdoor testbed, a trained researcher measured the height of 20 plants. The height of the corn from the ground to the top of the corn varies between 1.98m and 2.26m, with a mean height of 2.108m and a standard deviation of 8.28cm. The height from the ground to the tassel of the same plants ranged between 2.33 and 2.65m, with a mean of 2.51m and a standard deviation of 8.61cm. A 3×10m area was surveyed, which is the size of a typical agronomy phenotyping trial.

To evaluate the scanner in an outdoor setting, a total of $1,155$ scans were taken above the corn field in a sunny morning in August. The UAV is flown under manual control multiple times over each row in the area, at approximately the same speed. The laser scanner continuously scans the region, and the results from the scans are combined to form an estimate of the average height of the corn in the region. After restricting the sample angles to the central $90°$ arc, $295,680$ individual range readings were collected. Of these samples, over 96.5% are valid. The number of valid samples per scan is shown in Figure 5, as reported by the laser scanner's internal filtering process. At least 75% of the possible 256 range readings in the $90°$ arc are valid in each scan. Even when the number of valid samples drops, it quickly recovers, so the UAV did not encounter prolonged periods of bad scanner performance. The large number of range readings in each scan enables the construction of a well defined distribution, and potentially allows many samples to reach the ground in each scan. The number of valid samples in each scan shows that the small laser scanner, when properly placed, is effective in an outdoor setting.

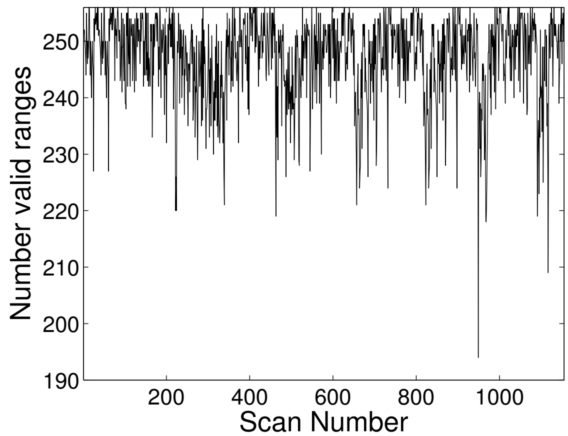


Fig. 5. Valid samples per scan

B. Indoor vs. Outdoor Data Comparison

We first compare the distributions produced from scans of outdoor data (shown in Figure 3(c)) to indoor data (shown in Figure 4(b)), to check if the same features are present in both testbeds. If both locations have similar types of distributions, it is likely that the same procedure for estimating crop height and UAV altitude will work in both locations.

Figure 4(b) shows the CDF of a scan taken in the indoor testbed. This figure shows the same sharp increase in readings, corresponding to the tops of the leaves, at a range of 0.9m to 1.1m, as the outdoor corn does. The layers of leaves cause the same gradual increase in the CDF, until the last layer is reached, as is seen in Figure 3(c). Finally, the samples that reach the ground cause a final sharp uptick in the CDF at long ranges, just as in the outdoor data. The similar shape of the two distributions suggests that the same crop height and altitude estimates can be used in both cases, even though the indoor testbed uses much shorter plants.

C. Crop Height Analysis

We now explore the effect of the input parameters p_g and p_c on the estimates of the crop height. Recall that p_g and p_c are parameters used to choose which samples represent the ground and the top of the crop.

Table I summarizes the impact of different values for p_g and p_c on the crop height estimate. The first row is the result of taking the two extreme points of each scan, highest and lowest, and using the difference as the crop height estimate. This produces unacceptable results, as the outdoor crop height estimate is 0.77m larger than the actual

p_g.	p_c	Est. Indoor Height (m)	Est. Outdoor Height (m)	Indoor Error (m)	Outdoor Error (m)
100	0	1.0545	2.8810	0.0875	0.7730
99	1	1.0412	2.5026	0.0742	0.3946
99	2	1.0335	2.4601	0.0665	0.3521
99	5	0.9888	2.3808	0.0218*	0.2728
95	1	1.0219	2.1849	0.0549	0.0769
95	2	1.0133	2.1440	0.0463*	0.0360*
95	5	0.9690	2.0625	0.0020*	−0.0455*
90	1	1.0040	1.9077	0.0370*	−0.2003
90	2	0.9956	1.8609	0.0286*	−0.2471
90	5	0.9514	1.7771	−0.0156*	−0.3309

TABLE I

IMPACT OF ESTIMATION PARAMETERS ON CROP HEIGHT ESTIMATES. VALUES WITH A * ARE UNDER THE 5CM OF ERROR REQUIREMENT.

crop height. This is the result of the tassels of the corn and tall corn leaves producing estimates of the plants' tops that are closest to the UAV. The ground estimate is also overestimated as it captures holes in the ground, and furrows in the field, producing long range scan estimates. The indoor data is similarly affected by noisy measurements, and overestimates the artificial plant heights. The height estimate is also unaffected by the imprecise manual control, which caused the UAV to repeatedly change its altitude over the field. Despite changing the UAV's position relative to the crop, the system was still able to form an accurate height estimate.

As more data is filtered from the scans, the crop height estimates converge to the actual values. Of particular interest are the values around $p_g = 0.95$, which produced a stable flight from the UAV. Using this parameterization, we can see that rejecting a small amount of the close scans to the UAV, $p_c = 0.02$, produces a crop height estimate that is within 4cm of the true value for the outdoor field. This parameterization also accurately estimates the indoor testbed's height.

Table I shows that the system is more sensitive to changes in p_g than to p_c in the outdoor setting. We conjecture that this is due to the dense upper canopy returns many samples that are a good estimator for the top of the crop. On the other hand, very few samples reach the ground, so the few samples reaching the ground have a high probability of being corrupted by variations in the ground, holes, debris, or even small plants growing in the field.

Intuitively, the parameters match the physical aspects of the outdoor field. The top layers of leaves form a dense canopy, with only a few protrusions by leaves and corn tassels. Only a small number of measurements in each scan will reflect from these surfaces, which means p_c can be very small. On the other hand, the ground readings are impacted by furrows in the field, and the generally uneven ground. This requires more noise rejection from the ground estimate, results in $p_g = 0.95$. Given that the corn was in good health, and mature, the canopy in the field is representative of the highly cluttered environments the UAV will operate in. Future studies will examine the impact of different fields on this parameterization.

VI. CONCLUSIONS AND FUTURE WORK

In this paper we have shown the feasibility of using a low cost laser scanner, mounted to a small UAV platform, to measure crop heights and control the height of the UAV over fields. With appropriate filtering and computation, the system is able to exploit small gaps in the crop foliage to directly sense the ground, which enables the UAV to fly at a fixed altitude, close to the crops. Flying close to the fields dramatically increases the spatial resolution of the data when compared to traditional measurements, and enables smaller and cheaper UAVs to be used in these missions.

In the future, we will exploit the laser scanner's ability to sense multiple levels of the crop canopy to generate multidimensional models of the field. These models can then be used to evaluate crop development and health. Additional sensors, such as a camera, will also be added to the system to allow agronomy researchers a better view of a field's development and health. The system will be tested on other crops to characterize the distribution of scan data for different plants. These new models will be used to adapt the existing hardware and software system to a larger variety of crops. Geo-referencing the combined data will enable new datamaps to be built, which will enable new insights into crop development and health.

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