3D Time-of-Flight camera-based sensor system for automatic crop height monitoring for plant phenotyping

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Abstract: In this paper a new method for automated measurement and monitoring of plant height and leaf count of single plants under field conditions, with the objective to develop an objective data source with a high comparability for plant phenotyping in field trials, will be presented. The morphological characterization of maize plants is performed by a statistical distance segmentation of the ground and the leave's height level and a skeleton representation of the plant's structure based on a data generated by a 3D Time-of-Flight camera. The functionality of the new method was proven and validated by online greenhouse measurements.

Keywords: 3D ToF camera, autonomous field robot, height monitoring, leaf count, plant phenotyping

1. INTRODUCTION

Phenotyping is the key technology for the evaluation of plants for plant breeding in field trials. The benefit of analyzing the information is the ability to develop strategies for new procedures in order to optimize plant quality and yield. Next to spectral information for a physiological analysis, one important part of these phenotyping methods is the exact measurement of the plant's morphological characteristics. Some of the central morphological parameters of interest for plant breeding are, for example, the plant's height and the leaf amount.

The analysis is typically performed by experts judging the field situation by characterizing random samples manually taken on the field plot. Since this analysis has to be done manually, it is very time consuming, generates high costs and has a varying reliability. Moreover, the phenotyping is performed by different experts, this may cause additional variations.

To overcome the disadvantages of the manual methods described above, the implementation of sensors, system technologies and complex algorithms for the development of methods for automatic phenotyping are of increasing importance. The benefits of such methods are the comparability of data sets, the objectivity of the data and the measurement in real-time on moving vehicles. Autonomous field robots are an outstanding option for the implementation of the automatic phenotyping methods. The combination of the advantages of the automatic plant characterization with an autonomous vehicle can be the first application for a field robot in agriculture.

Figure 1: Autonomous field robot BoniRob

According to this, the authors have recently presented an autonomous field robot for single plant based phenotyping (Ruckelshausen *et al.* 2009) called "BoniRob" (see Figure 1). With the usage of this robot objective data sets can be generated automatically of every single plant of the field while driving autonomously through the crop rows. Since the robot is able to detect and redetect every

single plant, it is possible to perform repeated measurements of different growth stages of the plants. This leads to time based data of the characteristics of the single plants within the field. The gathered data can be used by plant breeders to develop new strategies for the growth process.
To accomplish the autonomous phenotyping, the system architecture of the field robot BoniRob includes a navigation module for the control of the robot, a speed and steering module for the control of the motors and hydraulics of the robot, a phenotyping module for the calculation of plant parameters. Each of these systems is equipped with several different sensors supplying information to the control units. Besides a Hyper spectral imaging system, laser distance sensors, light curtains and a RTK GPS system, the phenotyping system is equipped with state-of-the-art 3D Time-of-Flight (ToF) cameras.
To measure the plant parameters, imaging systems with a high performance are needed. In agriculture commonly 2D RGB or gray scale camera systems were used for plant and leaf analysis. Besides the common one chip cameras, also multi chip cameras were used for the classification of weed species (Weis (2009)). For the measurement of the plants height stereo vision or laser scanner systems were used. A system for the measurement of the height of agricultural crops based on laser scanning was presented by Lumme et al. (2008)).
As a new approach for the combined online measurement of the plant's height and leaf count 3D ToF cameras will be used as a base for the calculation of the plant's morphological characteristics. 3D ToF cameras have recently been identified as a promising technology with a high potential for the automatic plant phenotyping by the authors (Klose et al. (2009)). Besides their ability to simultaneously generate 2,5D distance images and gray scale intensity images at real-time without additional calculations necessary, they have been proven to generate reliable and repeatable results for plant measurements under outdoor conditions. The distance images generated by these cameras can be used for a height based segmentation of the scenery. In this paper a sensor system based on 3D ToF cameras, integrated into the autonomous robot "BoniRob", for the automatic and contactless online measurement of crop height and leaf amount of maize plants in the early growth stages under laboratory and field conditions will be presented.

2. MATERIALS AND METHODS

For the development of the sensor system for the automatic geometrical measurement of maize plants the 3D ToF camera "CamCube3" (see Figure 2) by PMD Technologies with a resolution of 200 x 200 Pixels and an opening angle of 40° x 40° will be used. This camera is able to simultaneously generate a distance image, the related 3D point cloud, the intensity image and a flag image, indicating the possible saturation or low-signal state of the pixel. Since the information of the distance image is given in cycloid coordinates, the pixel coordinates need to be transformed into the Cartesian coordinate system. Another way is to generate a new distance image using just the z-information of the 3D point cloud. To correct the complex distance errors (Fuchs (2008)) of this camera a calibration was performed before the first measurements. Since the operation range for the measurements of the maize plants in early growth stages using the field robot BoniRob can be limited to a distance of maximum 80 cm and only one fixed integration time was used, a calibration using a look-up table containing the correct distances, as described by Kahlmann et al. (2006), was created.

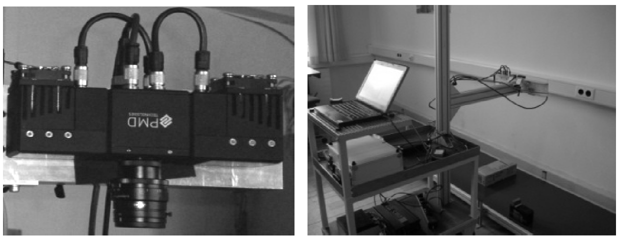

Figure 2: PMD CamCube3

For the development of the algorithms, the camera was mounted with a top-down field of view to a measurement rig (see Figure 2) for static and, in combination with a conveyor belt, for dynamic measurements of maize plants in the laboratory. The dynamic experiments were used to simulate a measurement run with the camera system attached to the field robot BoniRob.

2.1 Distance segmentation

With the images taken from a top-down perspective of the plants, the 2,5D distance images do not only contain the distances of the camera to plant, but also the measured distance to the underlying ground (see Figure 3). To be able to calculate the exact plant height it is reasonable to set the reference level to the ground's distance. Therefore a segmentation of the 2,5D raw image into a ground and a plant height level is necessary.

Figure 3: 2,5D raw distance image of maize plant

To determine the ground distance level within the 2,5D image, the histogram of all occurring distances is calculated. Afterwards, a kernel smoothing function (1), using the standard normal density function for k(t), is applied to this data, to calculate the kernel density estimate.

$$\widetilde{f_n}(t)=(1/n)\sum_{j=1}^{n} k_h(t-x_j) =(1/nh)\sum_{j=1}^{n} k\left(\left(t-x_j\right)/h\right) \quad (1)$$

The resulting density estimate, applied to the distance image of the maize plant of Figure 3 can be found in Figure 4. For the calculation a bandwidth *h* of 0.05 m with a *n* of 100 samples were used. During the development stage, these values have shown a good balance between a clear distinction of the ground and plant level and a detailed representation of the height distribution within the plant. Since the distance levels of the ground within the 2,5D image are in a very narrow bandwidth, the occurring distances sum up to a high peak within the density estimate. In contrast to this, the lower distances measured below this peak distance level do not have a uniform distribution. Within this distance area it is possible to detect small peaks. These peaks are a result of the different heights of the leaves of the plants. As a result, it is possible to divide the distance image into a plant and a ground level by setting a distance threshold taken from the kernel density estimate related to the image. According to this, the reference level for the height calculation will be set to this level.

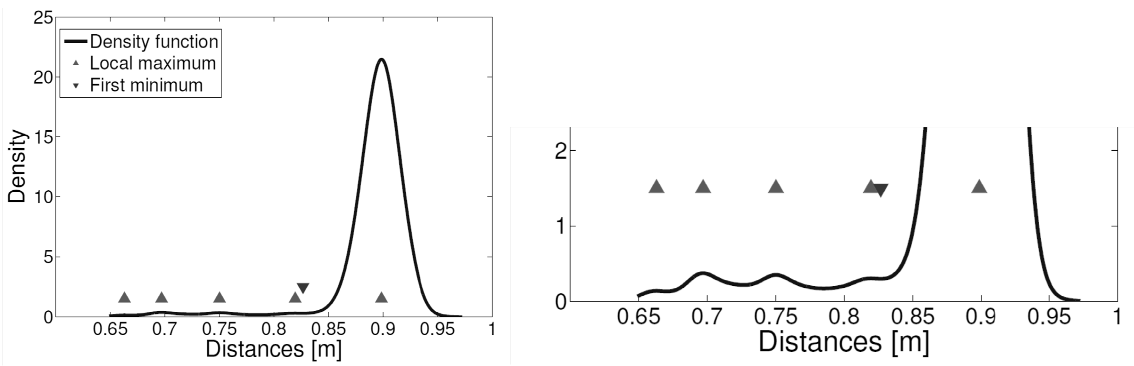

Figure 4: Kernel smoothing density estimate of the 2,5D distance values

2.2 Automatic height measurement

All distance values within 2,5D image will be subtracted by this value to calculate the height value above the artificial ground level. All distances exceeding this level are set to zero. The most reliable height data can be generated by choosing the threshold value to be equal to the position of the highest peak which can be considered to be the mean value of the distances to the ground. But since this would result in a mixture of plant and ground pixels, the most robust threshold value for excluding the ground is the last local minimum before the high ground peak. The end result is a height image of just the plant.

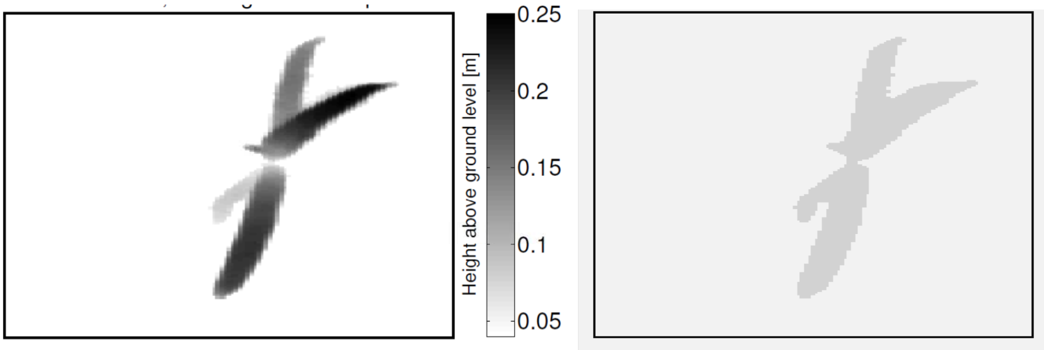

Figure 5: Height image of a maize plant and binary image of a maize plant

To correct the height data, the distance difference between the position of last local minimum and the one of the ground peak will be added to the image heights. To determine the height of the plant, the mean value of the 10 highest values found in the corrected height image is used, to reduce the effect of noise.

2.3 Automatic leaf count

Besides the calculation of the separation threshold, the kernel density estimate can also be used to determine the leaf amount of plants in early growth stages. Therefore the local maximums, standing for the different leaf's height, can be counted.
Another way to determine the leaf count of a maize plant of the target plant height up to 80 cm is by counting the endpoints of the leaves. To calculate the endpoints of the plant's leaves, a reduced graphical representation of the plant's structure, including the leaves and their endpoints, is needed. The first step is to generate a binary image from the corrected height image (see Figure 5).

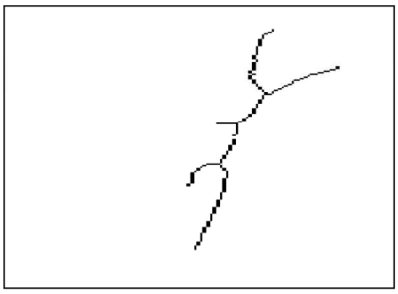

Figure 6: Skeleton of a maize plant

Therefore all pixels belonging to plants are set to a value of one and all the pixels belonging to the artificial ground level are set to a value of zero. The resulting edge represents the plant boundaries including the leaves endpoints. The next step is to calculate a reduced structural representation of the plant, by shrinking the binary area down to the skeleton of the plant. The skeleton in Figure 6 shows, that all leaves of the plant, even the small ones, are reduced to branches as long as the endpoints are visible in the binary image. These endpoints can now be found by checking the neighborhood of every pixel of the skeleton. As soon as only one neighboring skeleton pixel in a 3 x 3 area can be found, the actual pixel position can considered to be an endpoint of the skeleton's branch.
Besides the detection of leaf endpoints, the skeleton can also be used to detect the way the plant's leafs are overlapping. Therefore, the binary skeleton image, with a value of one for the skeleton and a value of zero for the rest, can be multiplied with the corrected height image. This multiplication results in a height profile of the skeleton

Assuming that all leaves consist of one branch point and one endpoint, it is possible to determine the leaves height level by calculating the maximum height occurring within the leaves related branch's height profile. If two of the neighboring branches have a height next to the branch point similar to the one of the branch point itself, these two branches can considered to be connected. Since these two branches must be on top, they will overlap all other branches connected to their branch point. The focus of further work is to count the leaves of two plants with overlap. Therefore the different leaves need to be assigned to the correct plants. A possible approach for the assignment of the leaves to a certain plant is to follow the height profile of the skeleton beginning at the leaves endpoint and continuing to the plants centre in order to find the centre branch point. To calculate the leaf area of the plant the ratio of plant pixel count to the ground pixel count using the binary image information of Figure 6 is used. This ratio is then multiplied to the ground area calculated by using (2) with an opening angel of the camera of φ=θ=40°.

$$A = 4 \cdot tan(\theta/2) \cdot tan(\phi/2) \cdot d^2 \quad (2)$$

2.4 Experiments

For the development and the calibration of the methods for a contactless measurement of the plant's height, leaf area and leaf count, 20 different maize plants of a height from 10 to 60 cm with a leaf count from 2 to 7 were used in the laboratory. To validate the new method, measurements using the target robot system BoniRob were performed in the greenhouse. As a reference, the plant height was measured using a laser distance measuring device and the leaves were counted manually. For the validation 124 maize plants with a height from 13 to 49 cm and a leaf count from 2 to 6 leaves were manually and automatically measured using the new method. To avoid overlaps, the spacing between the plants was about 30 cm. The results will be presented in the following paragraph.

3. RESULTS

In the following Figure 8 the results of the comparison between the measurement performed manually and the measurement performed by using the new method described in this paper is presented. Additionally a linear fitting function was calculated.

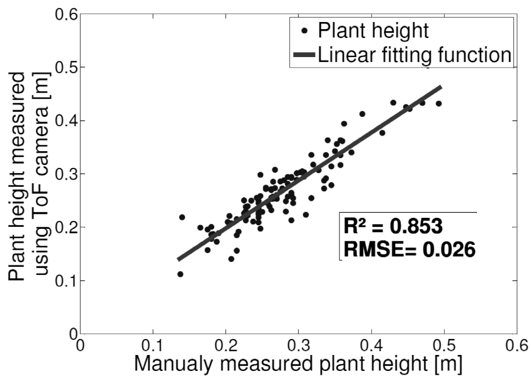

Figure 8: Plant height measured with new method vs. manually measured plant height

The visible variation of the values of Figure 8 is result of a combined measurement error caused by faulty manual measurements and the faulty automatic measurements. These can be a result of noisy camera images or possible wrong calculated thresholds for the distance segmentation of the image. The experiments have shown a high dependence of the quality of the image segmentation and the angle deviation to an orthogonal camera-ground alignment. In case of an angle change of the camera system the ground peak level in the kernel density estimate is decreasing while the peaks width is increasing. Since the plant's leaves peaks are, compared to the one of the ground, very low, the first leaf might disappear. In this case, the next minimum would be chosen to be the threshold level.

Still, the two methods have a good correlation with a R^2 of 0.853 and a very low root mean square error of 0.026. Thus, the proposed new method for contactless height measurement can be used for maize plants for an automatic plant phenotyping. To lower a possible effect on the height measurement quality caused by an angle deviation, the authors propose to perform an angle correction of the distance image. Therefore the normal vector of the ground level and its deviation to an orthogonal orientation needs to be calculated. To detect the ground layer, the RANSAC algorithm can be used by setting a plane as the desired mathematical model and defining the plants to be the measurement errors.The following tables are showing the result of the comparison between the manually counted leaf amounts and the leaf amount counted automatically by using the analysis of the kernel density estimate and of the maize plants skeleton.

Table 1: Result of the automatic leaf count using the skeleton method (right) and using the density estimate method (left)

RMSE=1,0		Calculated leave count (new method)					
		1	2	3	4	5	6
Leave count (manually)	2	1	10	3	1	0	0
	3	1	17	30	3	1	0
	4	0	3	12	17	3	2
	5	1	2	3	3	2	0
	6	0	1	2	3	3	0

RMSE=0,48		Calculated leave count (new method)					
		1	2	3	4	5	6
Leave count (manually)	2	0	15	0	0	0	0
	3	0	5	46	1	0	0
	4	0	3	4	29	1	0
	5	0	0	0	1	10	0
	6	0	0	0	0	1	8

Table 1 shows that the automatic leaf count based on the density function can only be used as an estimate of the leaf count for small plant up to four leaves. After this, it not possible to detect the peaks of single leaves because of their almost similar height level. In contrast to the density estimate method the automatic leaf count based on the skeleton method is showing a good result. With a root mean square error of only 0.48, almost all of the leaves in the given range where detected and counted correctly. The remaining errors, which in most of the cases occur below the true leaf count, result of completely overlapping leaves or parallel leaves. In this case the, if there is no two endpoints of the two leaves visible, the skeleton cannot split up and ends in only one endpoint. The analysis has shown that the two presented methods for the height measurement based on a kernel density estimate and the counting of the plant’s leaf based on a reduced structural representation using skeletons have a high correlation with the conventional manual method. Hence, these two methods can be used for an automatic height measurement and leaf count for maize plants. In combination with the autonomous field robot BoniRob, this system enables to perform an automatic monitoring of the two plant parameters of single plants under field conditions. The objective data generated by these methods can be used by plant breeders to develop new strategies for the growth process.

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