Simulating an Autonomously Operating Low-Cost Static Terrestrial LiDAR for Multitemporal Maize Crop Height Measurements

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Zusammenfassung: Im Zuge der Optimierung landwirtschaftlicher Prozesse in ökonomischer und ökologischer Sicht (Präzisionslandwirtschaft), sind Informationen zu pflanzenspezifischen Parametern (z.B. Wachstumsdynamik) unverzichtbar. Solche Informationen können mit einem Laserscanner erfasst werden. Allerdings ist deren Anwendung momentan durch hohe Beschaffungskosten und mangelnde standardisierte Methoden der automatischen Datenauswertung nur eingeschränkt sinnvoll. In der im Folgenden dargestellten Masterarbeit wird daher das Potenzial eines kostengünstigen, automatisch funktionierenden Laserscanners im Bereich Präzisionslandwirtschaft untersucht. Dazu werden Daten, die die multitemporale Wachstumsentwicklung von Maispflanzen beschreiben, aufgenommen und ausgewertet. Die Punktdichte der aufgenommenen Daten wird künstlich reduziert um einen kostengünstigen Laserscanner zu simulieren. Anhand dieser Daten werden rasterbasierte Höhenmodelle des Pflanzenbestandes berechnet. Die Ergebnisse zeigen eine hohe Genauigkeit im Vergleich zu Referenzpflanzen für Modelle, die basierend auf unreduzierten Daten berechnet sind (mittlere Abweichung = 0.02 m, Std. Abw. = 0.15 m, RMSE = 0.16 m). Wenn die Daten auf 2% ihres ursprünglichen Umfangs reduziert werden, um ein kostengünstiges Scan-System zu simulieren, verschlechtert sich die Genauigkeit (mittlere Abweichung = 0.12 m, Std. Abw. = 0.19 m, RMSE = 0.22 m). Die Ergebnisse zeigen, dass die Anwendung eines kostengünstige Scan-Systems mit einer Auflösung von bis zu 8 mrad (i.e., Punktabstand von 80 mm in 10 m Entfernung) in der Präzisionslandwirtschaft realisierbar ist. Die Masterarbeit liefert (a) umfassende Hinweise zum Scanner Aufbau sowie (b) eine Methode, die multitemporale Höhenmodelle des Pflanzenbestandes automatisch erstellt und auswertet.

1 Introduction

Light detection and ranging (LiDAR) has emerged as a powerful active remote sensing method for direct measurement of 3D plant structure in precision agriculture (LEE et al. 2010). The importance of 3D geodata in agriculture lies in its usability for plant modeling and plant-specific parameterization to monitor and improve crop management strategies (ROSELL & SANZ 2012). Applications include fertilization, irrigation management, yield estimation and optimization of harvesting processes (ZHANG et al. 2002).
Complexities caused by the outdoor agricultural environment, such as variable natural lighting, occlusion and obscuration of plant features by foliage from neighboring plants make an automatic observation of in-field variations challenging (MCCARTHY et al. 2010). Terrestrial laser scanning (TLS) provides a tool for generating a unique and comprehensive quantitative description of 3D plant and crop structure (PAULUS et al. 2014). TLS can be used to capture crop height, which is an important parameter for the local assessment and monitoring of crop types such as maize and wheat

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(Ehlert et al. 2010; Höfle 2014). Crop height responds to nutrients, water, and temperature and can be used as an indicator for external conditions of soil, weather, irrigation and fertilization (Omasa et al. 2007).

A TLS system can acquire multitemporal data such as crop height development when operating constantly and autonomously (ATLS). Such scanning systems can be emulated as a simplified low-cost version by mounting a laser rangefinder on a pan tilt unit, which automatically carries out horizontal and vertical scanning by rotating within predefined angles (Culvenor et al. 2014; Eitel et al. 2013). Such autonomously operating scanning systems capture multitemporal vegetation development, which adds time information to the 3D point cloud.

This study aims to identify specific requirements for a robust sensing system with automatically manageable data to improve precision agriculture applications. This is done by simulating a low-cost stationary TLS, which collects multitemporal crop height data. A workflow for processing and assessing ATLS data is developed. The workflow extracts the crop height development of maize by deriving crop height models (CHM), which represent the spatial crop growth pattern on a field level (Hoffmeister et al. 2009). The specific outcomes of this study are (a) clear requirements for a static ATLS system commendable for its successful use in precision agriculture and (b) a point cloud processing workflow for multitemporal monitoring of maize's crop height.

2 Materials and Methods

2.1 Study Area and Measurement Set-Up

A maize field in Heidelberg, Germany (49.43430° N, 8.65466° E, WGS84) served as the study area. The maize data were captured eight times over a period of 75 days starting on 28 May 2015 and ending on 10 August 2015. The measurements were conducted 40, 66, 75, 95, 100, 107 and 114 days after seeding, which took place on 18 April 2015.

For scanning maize crops a time-of-flight scanner VZ-400 (Riegl, Horn, Austria) with full-waveform echo detection was used. The system applies a near-infrared (1550 nm) laser beam with a beam divergence of 0.3 mrad and a range accuracy of 5 mm (one sigma) at 100 m. The system was installed on a water barrel to reduce occlusion effects, which was located at a field's edge.

Fig. 1: Scanner set up on stable barrel for elevated scanning at a height of 3.6 m, located at one edge of the monitored maize field.

This single scan position was used to simulate and determine the most cost-effective solution, since installation of each further scan position would raise the cost of the entire system. The scanner was registered to a global coordinate system in each scan campaign, since it could not be precluded that the simulated ATLS system would not change in position between measurements, as it had to be reinstalled for each measurement. To accurately register the ATLS position, a real time kinematic (RTK) GNSS base with a coordinate quality, on average, of 0.01 m was installed before each measurement on a known unchanging position. A RTK GNSS rover (Leica GS15) then captured the accurate position of the scanner.

Furthermore, two positions at the side of the field were chosen to set up tie point reflectors. They were fastened to metal poles that were secured about 30 cm into the ground. This allowed the re-establishment of the reflectors at the same position for each campaign. To verify this, the accurate position of the reflectors was measured with an RTK GNSS rover. In addition, the height and position of 140 plants along different transects in the field were measured manually with a measuring tape and a RTK GNSS rover each time. An overview of the measurement set-up is provided in Fig. 2.

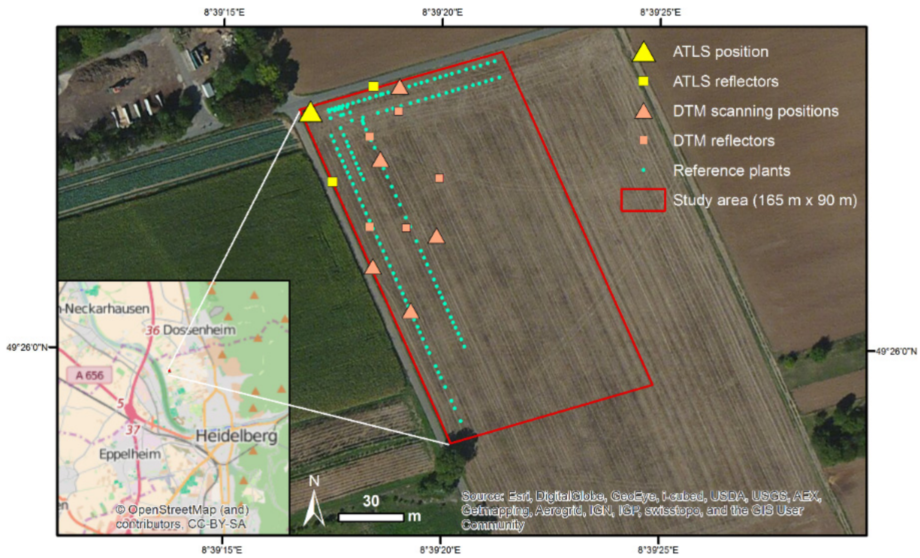

Fig. 2: Overview of measurement set-up located in Heidelberg (Germany) for simulation of autonomously operating terrestrial laser scanner (ATLS). Since the first campaign (t_1) aimed to gain data for a complete high-resolution digital terrain model (DTM), multiple scanning positions and reflectors were used. For the subsequent set-up of the simulated ATLS system (t_2 - t_8), only one scan position and two reflectors were used.

2.2 Generation of Crop Height Models

A crop surface model (CSM) represents the upper boundary of a crop field as an elevation value for deriving spatial crop growth patterns on a field level (HOFFMEISTER et al. 2009). A crop height model (CHM) represents the crop height by subtracting the DTM value from the maximum CSM elevation value per cell. The workflow of CHM generation (Fig. 3) aims to extract multitemporal CHMs with a cell size of 0.25 m x 0.25 m based on TLS measurements of different point densities. From the TLS data of the first campaign (t_1), a DTM for the study area was extracted. TLS data for each campaign (t_1 - t_8) were captured and registered to a common coordinate system. Then, point density was systematically decimated by keeping every n^{th} emitted laser beam according to its timestamp with increasing step width *n*, i.e., *n* = 0 to *n* = 50 at increments of 2 (HÄMMERLE & HÖFLE 2014). This allows the simulation of ATLS systems with different scanning capabilities in terms of point density. From these datasets, CHMs were derived by calculating the difference between CSM per campaign (t_1 - t_8) and the DTM from the first campaign (t_1). The workflow is based on modules of the software Orientation and Processing of Airborne Laser Scanning data (OPALS) (PFEIFER et al. 2014), which are merged in an automatically executable Python script (*Link to the script that contains crop height modelling and assessing steps*).

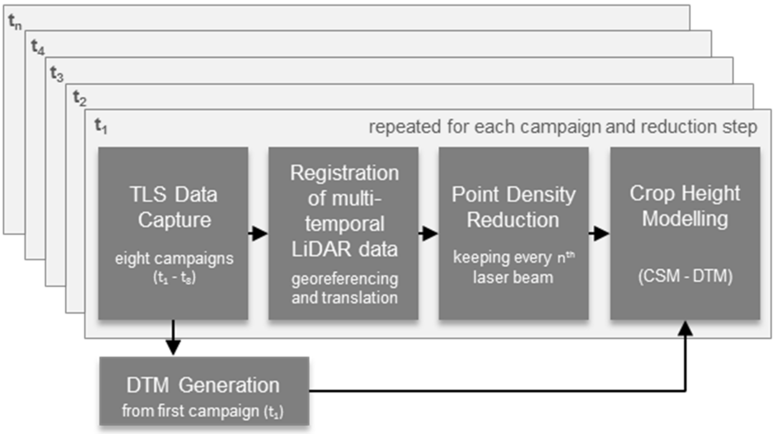

Fig. 3: Workflow of crop height model (CHM) generation from TLS data capture to CHMs calculation from reduced point density data sets.

2.3 Accuracy Assessment of Crop Height Models

As for CHM accuracy assessment, the manually measured height at 140 unchanging reference plants was compared to corresponding CHM cell values. If a reference plant was within a CHM cell, the difference between CHM height and the manually measured height of the reference plant was captured as Δh. Factors influencing Δh were statistically investigated by calculating Pearson's coefficient of determination (R^2) between Δh and distance to the scanner as well as between Δh and point density. This information helps to decide on parameters such as distance to scanner and point density when constructing an ATLS set-up for crop height measurements.

3 Results and Discussion

3.1 Generation of Crop Height Models

After registering multitemporal TLS data from eight point clouds (t_1 - t_8), the difference of coordinate pairs in all scans varies 0.001 m (x), -0.001 m (y) and 0.024 m (z), on average. This accuracy is similarly low as obtained by Tilly et al. (0.06 m and 0.01 m) for aligning multitemporal scans of rice crops (TILLY et al. 2015) and 0.04 m for scans of barley crops (TILLY et al. 2015).
Whilst the first reduction step (*n* = 2) leads to a reduction of about 50% (7,388,193 points) of the original point cloud, the final reduction step (*n* = 50) leads to a reduction of 98% (333,773 points). All point clouds resulting from step widths *n* > 10 result in a reduction between 2% and 10%. The reference scans, which were captured with a lower scan resolution, show a similar point count development. The artificial reduction of point density leads to similar results considering the point count of reference scans in (HÄMMERLE & HÖFLE 2014).

3.2 Accuracy Assessment of Crop Height Models

Calculated heights in CHMs are close to those manually measured regardless of point density reduction until approximately 95 days after seeding and a crop height of 2.3 m (Fig. 4). The unreduced dataset (n = 0) leads to the smallest difference between manually measured reference plants and CHM based crop heights.

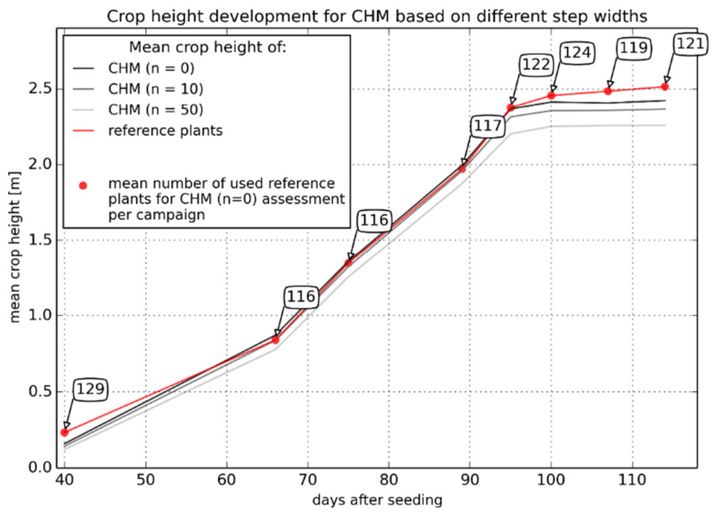

Fig. 4: Crop height development based on CHMs for step width n = 0 (i.e., no artificial reduction), n = 10 (10% of data remaining) and n = 50 (2% of data remaining) and on manually measured reference plants. These are only used for calculation of Δh if a CHM cell contains a value at their location. Connecting lines do not indicate linear crop growth.

The development of Δh for the CHMs shows that a reduction of point density leads to a decrease in accuracy, with Δh augmenting with increasing crop height (Fig. 5).

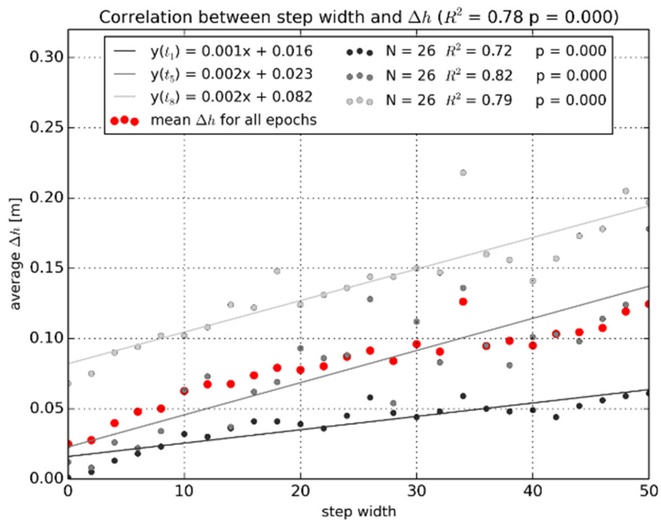

Fig. 5: Accuracy of CHM at 40 (t_1), 95 (t_5) and 114 (t_8) days after seeding based on point clouds reduced with different step widths (n = 0, i.e., no artificial reduction to n = 50, i.e., 2% of data remaining). The points belonging to a specific campaign, show Δh averaged per step width and are summarized in a line of regression in the same color (y). Each campaign encompasses 26 Δh values, i.e., one for each step width from n = 0 to n = 50 at increments of 2. Pearson's coefficient of determination (R^2) and p value (p) are additionally added.

Overall, the unreduced data ($n = 0$) leads to high accuracy values for Δh (mean deviation = 0.02 m, std. deviation = 0.15 m, RMSE = 0.16 m). This accuracy decreases when reducing the point cloud with step width n = 50, i.e., 2% of data kept (mean deviation = 0.12 m, std. deviation = 0.19 m, RMSE = 0.22 m). These results for n = 50 can be expected for a maximum distance of 100 m (150 m for n = 0, i.e., no artificial reduction) between scanner and crops.

These findings permit some general statements about the minimum ATLS point density needed for the monitoring of maize and structurally similar crops. As stated in (HÄMMERLE & HÖFLE 2014), the scan resolution applied needs to be set in accordance to crop stand features such as crop type, fertilization stage, growth stage and required accuracy. Additionally, it has to be mentioned that the artificial reduction of point density simulates a low-cost ATLS system only to a certain extent. High-resolution scans used as a basis for reducing point density have a high penetration rate. Subsequently, conducted point clouds of reduced point density encompass points of laser beams that would not have been captured in the case of a real low-resolution scan as applied in (EITEL et al. 2013; GLENNIE & LICHTI 2010).

4 Conclusion and Outlook

This study shows that LiDAR technology in general and multitemporal 3D geodata in particular are feasible for application in precision agriculture. No reduction of the original points cloud (n = 0) results in an accuracy of 0.02 m, a reduction of 90% (n = 10) results in an accuracy of 0.06 m and a reduction of 98% (n = 50) results in an accuracy of 0.12 m. The last reduction step corresponds to a scan resolution of 8 mrad, i.e., point spacing of 80 mm at 10 m distance.

It can be concluded that models and applications that use RMSE of Δh are robust against reducing scanning resolution. CHM's accuracy measured via Δh decreases for later measurements when crops are higher than 2.3 m, because occlusion effects appear more often. The scanner height should be chosen according to maximum crop height in order to optimize the accuracy. The workflow developed, which automatically derives and assesses CHMs is reusable in a multitude of further studies and application scenarios. Analogously, it could be refined to process multitemporal 3D geodata for monitoring environmental changes (e.g. landslides, snow cover or glaciers).

Further research could investigate the transferability of the approach by using a real low-cost laser scanning system as in (EITEL et al. 2013) based on the specific outcomes of this study. The transfer of the results to additional crops (e.g. wheat, rye or rice), crop parameters (e.g. plant volume or nutrient content) and different measurement set-ups (e.g. mobile vs. static) could be investigated to complement and enhance knowledge about the potential of a TLS in PA.

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