Development of a Robotic Crop Phenotyping Testbed for Sustainable Agriculture

Ali Imran[1*], Muhammad Owais Tahir[1*], Muhammad Shabbir Hasan[1], Abubakr Muhammad[1]

[1]NCRA Agricultural Robotics Lab
Center for Water Informatics and Technology
Lahore University of Management Sciences (LUMS), Pakistan
{ali_imran, tahir_muhammad, muhammad.hasan, abubakr}@lums.edu.pk

Abstract

To meet the food demands of increasing global population, it is essential to make advancements in the field of genomics and plant phenotyping to explore novel traits in plants. This would require developing automated phenotyping methods which are efficient, and less prone to human error and bias. This paper presents the work on development of a robotic platform, equipped with a diverse set of sensors, enabling it to gather a rich data set of essential parameters required for digital phenotyping. The goal of the project is to aid small scale farmers, with limited resources, to adopt sustainable agricultural practices and optimize the yield of their products.

Introduction

With the increase in global population, demand for agricultural crops is increasing and may continue to increase for coming decades. (Tilman et al. 2011) forecasts a 100-110% increase in the demand of the three cereal crops (wheat, maize and rice) from 2005 to 2050. Although, advancements in crop breeding and agronomics have resulted in the increase of cereal crops by a factor of 3 (Pingali 2012), the annual yield increase targets are still not being achieved through traditional breeding programs (Tester and Langridge 2010). Thus, the challenge is to adopt sustainable agricultural practices by integrating and utilizing modern, state of the art technologies in order to increase the yield of the crop field and improving the overall quality of the crop.

The aforementioned issue highlights the need of making advancements in genotyping and phenotyping to discover novel traits in plants and increase the available genetic diversity of existing traits (Virlet et al. 2016). In order to accelerate the progress in the field of plant genomics, it is essential to address the issue of "Phenotyping Bottleneck" (Furbank and Tester 2011). Conventional phenotyping methods rely on physical intervention by humans, which has several disadvantages. It is labor intensive, time consuming, as well as highly prone to human bias and error. Thus, adopting an automated process to monitor crop morphology over its cultivation period can have significant impact on the end product. Automated phenotyping process usually involves the deployment of a robotic platform equipped with relevant sensory equipment. To date, a number of phenotyping platforms have been developed, including aerial solutions, controlled environment based solutions and several ground based system. Table 1 summarizes and presents a comparison between some of the existing datasets and our dataset.

Based on the information above, the importance of analyzing crop morphology cannot be understated. Understanding the health and growth parameters of the crops form the basis of crop breeding and modern agriculture. While the domain of computer vision, machine learning and deep learning has matured enough to provide solutions on the algorithmic side, very limited efforts have been made to develop large enough datasets on which to feed these algorithms. (Chebrolu et al. 2017) created a 5TB dataset, comprising of data from multiple sensors deployed on a mobile robotic platform inside a sugar beet field. However, the basic purpose of this dataset was to aid in the development of a robotic platform for autonomous localization and mapping inside an agricultural field. (Khanna et al. 2019) presents a high quality, rich dataset for plant phenotyping under stress environments. The point clouds within the datset are top down representation of the plant, thus, providing with only 2.5D data. Addressing this issue (Schunck et al. 2021) provides with a valuable dataset comprising of 3D point points of plants. However, the data collected is within a controlled environment-setup. Although, several mobile robot platform have been developed with the sole purpose of creating large datasets such as (Bender, Whelan, and Sukkarieh 2020) and (Pire et al. 2019), these robots have limited onboard sensors.

This project focuses on the development of a cable-driven in-field deployable robotic platform which is equipped with a diverse set of sensors, enabling it to gather important spatio-temporal data essential for plant phenotyping, along with data required for autonomous localization and navigation within an agricultural field. Moreover, this project focuses on developing a product aimed to assist small scale farmers adopt sustainable farming practices and optimize the yield of their products. The following sections cover the technical details of the project, focusing on how this robotic platform would provide an all-rounded solution to address the issues mentioned above.

*These authors contributed equally.

Copyright © 2022, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

Table 1: Literature survey of agricultural datasets collected from digital phenotyping platforms.

Name	Type	Sensors	Vehicle	Application
Rose-X (Dutagaci et al. 2020)	Indoor	X-ray Tomograph	Handheld	Segmentation and Classification
Pheno4D (Schunck et al. 2021)	Indoor	Light Section Scanner	Light Scanner on Articulated Arm	Phenotyping
FieldSAFE (Kragh et al. 2017)	Outdoor	Stereo camera Thermal camera Web camera 360○ camera LiDAR Radar IMU and GPS	Tractor Mounted Sensors	Obstacle detection
DeepWeeds (Olsen et al. 2019)	Outdoor	Camera	Handheld	Deep Learning Based Classification of weeds
CropDeep (Zheng et al. 2019)	Outddor	Camera	Handheld	Deep-Learning-Based Classification and Detection
BoniRob (Chebrolu et al. 2017)	Outdoor	GPS LiDAR Kinect JAI Camera	Ground Robot	Classification, localization and mapping
(Di Cicco et al. 2017)	Outdoor	RGBD-NIR JAI	Ground Robot	Deep Learning based crop and weed detection
(Haug and Ostermann 2014)	Outdoor	Camera	Ground Robot	Precision Agriculture
LUMSpheno	Outdoor	3D-LiDAR Multispectral Camera GPS IMU	Fixed-line Over-head Robotic Platform	Lidar based Phenotyping Precision Agriculture Localization and Mapping

Methodology

Data Acquisition System

The data acquisition system under development for crop phenotyping mainly consists of four major components along with the carrying robotic overhead platform. The details of components and their respective functions are explained in following subsections.

Robotics Platform The concept of digital non-invasive phenotyping has been popular since last decade and many robotic phenotyping platforms and techniques have been developed, each having their own set of advantages and disadvantages. (Deery et al. 2014). These platforms are mostly hosted on UAVs or ground robotic vehicles which enables rapid acquisition of data with independence in location and movement paths. However, in case of UAVs, the number of sensors which can be mounted is limited amid payload capacity limitations. Moreover, resolution is also affected by external environmental factors and altitude (Sankaran et al. 2015). Certain cable driver approaches have been adopted. (Bai and Ge 2021) and (Virlet et al. 2016) present state-of-the-art platforms which cover large agricultural fields. However, these platforms have huge setting up costs.

Alternatively, ground vehicles have also been developed for agricultural purposes. (Young, Kayacan, and Peschel 2019) presents a UGV which acquires crop data from above and below the canopy. (Kayacan, Zhang, and Chowdhary 2018) presents another unique robotic platform which is 3D printed which traverses within a corn field accumulating vluable data. Ground based autonomous vehicles can host large number of sensors and can provide higher resolution of images however, these require some kind of supervision as they move across uneven terrains independently.

Addressing the aforementioned issues, a unique approach has been adopted. Two poles of equal height have been fixed at either sides of the crop bed, connected by a high strength metal wire. The drive mechanism of the robot consists of a high torque motor with a pulley mechanism which can be easily mounted on the metal wire. This drive mechanism is attached with the rest of the robot chassis, thus making the complete assembly highly portable. This particular setup has certain advantages over other commonly used platforms. It can carry more payload, has a fixed, 1D motion path - minimizing the error in aligning repeated measurements and reduces the overall deployment cost. Choice of such platform for this task also complements the agriculture practices of sustainable intensification (Petersen and Snapp 2015), which includes using raised beds, mulching, intercropping and no tilling as shown in Figure 1. All of the sensors described in subsequent sections are mounted on this overhead robotic platform which moves over a line between two poles. The height of the platform is set to 3m which can be changed according to the cultivated crop height. The robotic platform is being developed to perform automated scans with regular intervals while recording environmental parameters, i.e. temperature and humidity before taking each scan. Figure 2 shows the platform in its complete state.

LiDAR LiDAR has been previously used in plant phenomics but its full potential in plant phenotyping is one of the field which is currently being actively explored (Zhang

Figure 1: Deployment agricultural site with implementation of sustainable intensification, mulching, raised beds and no tilling

.

and Grift 2012). Most of the LiDAR-based vegetation observation platforms developed are directed at one or two botanical properties for a small variety of plant species. In reality, the capabilities of LiDAR for botanical mapping go much beyond just mapping of the plant fields and measurements. In theory, LiDAR-based field phenotyping from the foliage to the canopy level can provide a wealth of helpful information for plant condition assessment and crop management (Guo et al. 2018). For example, it is typically difficult to detect the levels of water stress non-destructively; however, the LiDAR-based technique has demonstrated the ability to detect water shortages by measuring the degree of leaflet drooping by estimation of leaf area and tilt angle (Hosoi, Nakabayashi, and Omasa 2011).

The primary use of LiDAR is to provide 3D structural data of vegetation, which aids in high-throughput phenotyping by eliminating the perception effect that is frequently seen in 3D reconstructions using stereo photography. Acquiring 3D data with LiDAR is highly time efficient, as it typically takes only a few minutes for each scan. Despite such brief measurement times, a number of canopy characteristics such as leaf area, leaf tilt angle, LAI, and leaf area density (LAD) can be extracted (Lin 2015).

The LiDAR used in our system is Velodyne VLP-16 3D which is capable of capturing high resolution 360-degree scans at the rate of Up to 600,000 Points per Second with range of 100m. It is mounted in front of overhead trolley at 90-degree angle to provide top down view of the vegetation. The field of view captured at any instance is 20 degrees with range of -10 to 10 degree from center line. A LiDAR scan from the experimental field is shown in Figure 3.

Multi-spectral Camera The multispectral imaging approach can retrieve information spectrum of every pixel in a captured image with both fine wavelength precision and a large wavelength range. Spectral signatures can provide information about the qualities of an objects in the captured image. Plant reflection spectra may include data about their physiological circumstances and may thus be utilised to recover plant biochemical parameters or analyze plant development and disease traits. This technique has been popular in remote phenotyping over large areas through the usage of UAVs and has proven to successfully detect multiple traits

Table 2: Specifications of sensors being used on robotic phenotyping platform.

Sensor/Make	Specifications
LiDAR/ Velodyne VLP-16, PUCK Hi-RES	± 10° Vertical FoV Dual Returns 16 Channels 100m Range Up to ~600,000 Points per Second 360° Horizontal FOV
Camera/ MicaSense ALTUM	Blue, green, red, rededge, NIR LWIR: thermal infrared 8-14um Sensor resolution: 3.2MP GSD: 5.2 cm per pixel Capture Rate: 1 capture/second FoV: 48º x 37º Focal Length: 8 mm
GPS/ Stonex S900	Channels: 600 GPS: L1 C/A, L1C, L2C, L1P, L2P, L5 GLONASS: L1 C/A, L1P, L2C, L2P BeiDou: B1, B2, B3 Galileo: E1, E5a, E5b QZSS: L1 C/A, L1C, L2C, L5 SBAS: L1, L5 L-Band Position Rate:5 Hz, optional 20 Hz Signal Reacquisition:<1 sec RTK Signal Initialization: <10 s
IMU/ Razor IMU 9DoF	9DoF single Flat Board Tripple Axis Gyroscope 13-bit, tripple axis accelerometer Serial stream of output

and functional features of plants such as water content, surface temperature and salt stress (Pourazar, Samadzadegan, and Dadrass Javan 2019)

The multi-spectral camera imaging in our data acquisition system is carried out by MicaSense ALTUM mounted in downward facing configuration on the platform. The sensor is comprised of five camera and provides 5 discrete bands of images, namely: Blue (475nm), Green (560nm), Red (668nm), RedEdge (717nm) and Near Infrared (842nm). The unit also incorporates an integrated GPS unit for geoforcing the images with precise location information in the scanning field. The imagery is produced at 1 capture per second (12-bit RAW). A multispectral image from platform can be seen in Figure 3.

Localization and Positioning A GPS-RTK unit and IMU units are utilized to accurately record the precise pose, location and altitude of the laser scans. This is done in order to generate redundancy in terms of accurate point cloud registration as single sensor based positioning is always at disadvantage. GPS will be strongly influenced by the signal intensity and is prone to failure in case of signal obstructions. LiDAR is also capable of producing accurate odometry information but its performance can be easily degraded by external environmental factors. Internal Navigation sys-

Figure 2: Portable robotic platform with Lidar, multispectral camera, GPS and IMU mounted.

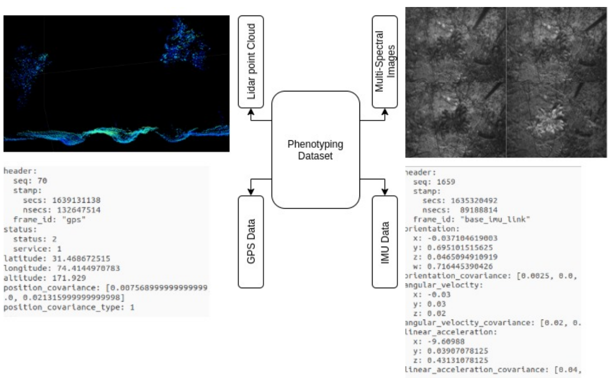

Figure 3: Details of collected dataset for phenotyping: accurate GPS data (centimeter level accuracy), high resolution multispectral images and dense pointcloud with IMU data.

tems such as IMU on the other hand is prone to the accumulation of error over time (Lan et al. 2015). Thus, the combination of LiDAR and IMU is utilized in the system which can learn from each other to provide a highly accurate positioning data for the registration of point cloud. The details of GPS and IMU units are provided in Table 2.

Computational Platform and Software The data acquisition system is using Nvidia-TX2 as computational platform and ROS (Robot Operating System) for integrating and recording all of the sensors attached. The computational platform is chosen as it is using ARM CPU which are best known for their power efficiency. This is important as whole robot is powered by LiPo batteries including driving motors, PC and sensors. Furthermore, no data processing is carried onboard the robotic platform, rather, it serves as data collection and transferring client. ROS provides open-source libraries for most of the sensors used in this system, opening the opportunity of further development and manipulation of data.

Data Structure and Storage

Beginning with germination, the data collection is progressed over complete cultivation period to encompass all growth phases of the crops, as well as record the fluctuations in field's conditions during the development phase. During the first data harvesting stage, the robotic platform scans the farm various times for repeated measurements. The collection also includes information on climate and ground conditions spanning from bright and clear to cloudy and damp. However, because the platform is not yet weather resistant, no data is being collected in rainy conditions.

The recorded data from platform is in the form of *.bag* files which contains the topics of GPS, IMU, spectral images and point clouds from lidar. Each file tagged with respective time, date, temperature and humidity information. Currently, this data is being stored on online storage which is accessible to team only. For the development of public dataset, a public NAS (Network Attached Storage) is under development which will serve as portal of automatic storage. Each scan will be uploaded to the storage automatically after acquisition with specific naming scheme described above.

Discussion

This paper presents the progress on the development of a robotic testbed which has the prospects of accelerating research in plant phenotyping, thus, contributing towards advancement in plant genomics research. The sensor suite provides feature rich data (7-10 GB of data per rosbag), as shown in Figure 3, stored in the form of rosbags allowing it to be converted in any format required using publicly available libraries and packages.

The aforementioned robotic platform has been deployed at a model agricultural site, adhering to the concepts of sustainable intensification and intercroping. Moreover, farming is being conducted on raised beds, without tillage and with the implementation of mulching, i.e. modern and environmental friendly farming practices have been adopted. This model farm produces a number of organic products. While the raised beds are mainly used for wheat harvesting, it also supports the growth of several strawberry runners. Moreover, the farm also houses an orchard of oranges and other seasonal fruits.

Although these farming practices have increased the overall productivity of the field, it also poses technical challenges. The dataset acquired from the field contains 3D data of all plant types produced in the farm. Isolating and extracting data of a certain crop becomes an uphill task.

Certain enhancements to this testbed can make this project more impactful. Incorporating a network of sensors to monitor the environmental parameters (ozone levels, soil moisture values, weather conditions) in the field can further aid in the plant morphological analysis. The future work entails the deployment of several IoT devices within the farm and integrating it with the robotic platform, making the dataset more comprehensive and complete.

References

Bai, G. F.; and Ge, Y. 2021. Cable Suspended Large-Scale Field Phenotyping Facility for High-Throughput Phenotyping Research. In *High-Throughput Crop Phenotyping*, 39–53. Springer.

Bender, A.; Whelan, B.; and Sukkarieh, S. 2020. A high-resolution, multimodal data set for agricultural robotics: A Ladybird's-eye view of Brassica. *Journal of Field Robotics*, 37(1): 73–96.

Chebrolu, N.; Lottes, P.; Schaefer, A.; Winterhalter, W.; Burgard, W.; and Stachniss, C. 2017. Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. *The International Journal of Robotics Research*, 36(10): 1045–1052.

Deery, D.; Jimenez-Berni, J.; Jones, H.; Sirault, X.; and Furbank, R. 2014. Proximal remote sensing buggies and potential applications for field-based phenotyping. *Agronomy*, 4(3): 349–379.

Di Cicco, M.; Potena, C.; Grisetti, G.; and Pretto, A. 2017. Automatic model based dataset generation for fast and accurate crop and weeds detection. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 5188–5195. IEEE.

Dutagaci, H.; Rasti, P.; Galopin, G.; and Rousseau, D. 2020. ROSE-X: an annotated data set for evaluation of 3D plant organ segmentation methods. *Plant methods*, 16(1): 1–14.

Furbank, R. T.; and Tester, M. 2011. Phenomics–technologies to relieve the phenotyping bottleneck. *Trends in plant science*, 16(12): 635–644.

Guo, Q.; Wu, F.; Pang, S.; Zhao, X.; Chen, L.; Liu, J.; Xue, B.; Xu, G.; Li, L.; Jing, H.; et al. 2018. Crop 3D—a LiDAR based platform for 3D high-throughput crop phenotyping. *Science China Life Sciences*, 61(3): 328–339.

Haug, S.; and Ostermann, J. 2014. A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. In *European conference on computer vision*, 105–116. Springer.

Hosoi, F.; Nakabayashi, K.; and Omasa, K. 2011. 3-D modeling of tomato canopies using a high-resolution portable scanning lidar for extracting structural information. *Sensors*, 11(2): 2166–2174.

Kayacan, E.; Zhang, Z.-Z.; and Chowdhary, G. 2018. Embedded High Precision Control and Corn Stand Counting Algorithms for an Ultra-Compact 3D Printed Field Robot. In *Robotics: Science and Systems*.

Khanna, R.; Schmid, L.; Walter, A.; Nieto, J.; Siegwart, R.; and Liebisch, F. 2019. A spatio temporal spectral framework for plant stress phenotyping. *Plant methods*, 15(1): 1–18.

Kragh, M. F.; Christiansen, P.; Laursen, M. S.; Larsen, M.; Steen, K. A.; Green, O.; Karstoft, H.; and Jørgensen, R. N. 2017. Fieldsafe: dataset for obstacle detection in agriculture. *Sensors*, 17(11): 2579.

Lan, H.; Yu, C.; Zhuang, Y.; Li, Y.; and El-Sheimy, N. 2015. A novel kalman filter with state constraint approach for the integration of multiple pedestrian navigation systems. *Micromachines*, 6(7): 926–952.

Lin, Y. 2015. LiDAR: An important tool for next-generation phenotyping technology of high potential for plant phenomics? *Computers and electronics in Agriculture*, 119: 61–73.

Olsen, A.; Konovalov, D. A.; Philippa, B.; Ridd, P.; Wood, J. C.; Johns, J.; Banks, W.; Girgenti, B.; Kenny, O.; Whinney, J.; et al. 2019. DeepWeeds: A multiclass weed species image dataset for deep learning. *Scientific reports*, 9(1): 1–12.

Petersen, B.; and Snapp, S. 2015. What is sustainable intensification? Views from experts. *Land use policy*, 46: 1–10.

Pingali, P. L. 2012. Green revolution: impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, 109(31): 12302–12308.

Pire, T.; Mujica, M.; Civera, J.; and Kofman, E. 2019. The Rosario dataset: Multisensor data for localization and mapping in agricultural environments. *The International Journal of Robotics Research*, 38(6): 633–641.

Pourazar, H.; Samadzadegan, F.; and Dadrass Javan, F. 2019. Aerial multispectral imagery for plant disease detection: Radiometric calibration necessity assessment. *European Journal of Remote Sensing*, 52(sup3): 17–31.

Sankaran, S.; Khot, L. R.; Espinoza, C. Z.; Jarolmasjed, S.; Sathuvalli, V. R.; Vandemark, G. J.; Miklas, P. N.; Carter, A. H.; Pumphrey, M. O.; Knowles, N. R.; et al. 2015. Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review. *European Journal of Agronomy*, 70: 112–123.

Schunck, D.; Magistri, F.; Rosu, R. A.; Cornelißen, A.; Chebrolu, N.; Paulus, S.; Léon, J.; Behnke, S.; Stachniss, C.; Kuhlmann, H.; et al. 2021. Pheno4D: A spatio-temporal dataset of maize and tomato plant point clouds for phenotyping and advanced plant analysis. *Plos one*, 16(8): e0256340.

Tester, M.; and Langridge, P. 2010. Breeding technologies to increase crop production in a changing world. *Science*, 327(5967): 818–822.

Tilman, D.; Balzer, C.; Hill, J.; and Befort, B. L. 2011. Global food demand and the sustainable intensification of agriculture. *Proceedings of the national academy of sciences*, 108(50): 20260–20264.

Virlet, N.; Sabermanesh, K.; Sadeghi-Tehran, P.; and Hawkesford, M. J. 2016. Field Scanalyzer: an automated robotic field phenotyping platform for detailed crop monitoring. *Functional Plant Biology*, 44(1): 143–153.

Young, S. N.; Kayacan, E.; and Peschel, J. M. 2019. Design and field evaluation of a ground robot for high-throughput phenotyping of energy sorghum. *Precision Agriculture*, 20(4): 697–722.

Zhang, L.; and Grift, T. E. 2012. A LIDAR-based crop height measurement system for Miscanthus giganteus. *Computers and electronics in agriculture*, 85: 70–76.

Zheng, Y.-Y.; Kong, J.-L.; Jin, X.-B.; Wang, X.-Y.; Su, T.-L.; and Zuo, M. 2019. CropDeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture. *Sensors*, 19(5): 1058.