Vinobot and Vinoculer: From Real to Simulated Platforms

Ali Shafiekhani[1]; Felix B. Fritschi[2] and Guilherme N. DeSouza[1]
[1]ViGIR Lab, Dept. of Electrical Engineering and Computer Science
[2] Division of Plant Sciences
University of Missouri, Columbia, MO, USA
Email: AShafiekhani@mail.missouri.edu, FritschiF@missouri.edu, DeSouzaG@missouri.edu

***Abstract*—In this work, a new element of our research for autonomous plant phenotyping is presented: a simulated environment for development and testing. As explained in our previous work, our architecture consists of two robotic platforms: an autonomous ground vehicle (Vinobot) and a mobile observation tower (Vinoculer). The ground vehicle collects data from individual plants, while the observation tower oversees an entire field, identifying specific plants for further inspection by the ground vehicle. Indeed, while real robotic platforms for field phenotyping can only be deployed during the planting season, simulated platforms can help us to improve the various algorithms throughout the year. In order to do that, the simulation must be designed to mimic not only the robots, but also the field with all its uncertainties, noises and other unexpected circumstances that could lead to errors in those same algorithms under real conditions. This paper details the current state in the implementation of such simulation. It describes how the target navigation algorithms are being tested and it provides the first insights on the functionality of the simulation and its usefulness for testing those same robotic platforms.**

I. Introduction

Population increases, climate change, degradation and loss of arable land, and the appearance of new pests and diseases threaten the world's food supply [1]. Understanding how plants respond to environmental and genetic perturbations can have an enormous social impact, as it is essential to accelerate crop improvement and agricultural management practices [2]. Crop improvement requires the identification and measurement of agronomically important phenotypes. To unravel molecular mechanisms, track genes through genetic crosses, and determine which interactions between the genotypes and their environments produce the desired phenotypes, geneticists and plant breeders must be able to reproducibly identify phenotypes that are likely to confer agricultural, environmental, and/or nutritional benefits. Truly high-throughput phenotyping will provide an unprecedented opportunity to study the physiological, developmental, and molecular mechanisms that govern the dynamic behavior of plants [3].

Until recently, the characterization of plant phenotypes has been a task for human eyes, legs, and brains. Conveyor belts, installed in greenhouses to transport potted plants to a phenotyping station equipped with cameras, represent the next state of the art in scoring phenotypes by algorithmic analysis of images. These algorithms relied (rely) on relatively uncluttered images: well-separated, young plants that easily can be rotated to help resolve lighting and occluding features [4]. But there are two fundamental flaws with guiding crop improvement only with greenhouse observations. First, phenotypes of crops grown in a greenhouse are often very different from those grown in the field. Phenotypes, such as disease resistance and robustness to environmental stresses, must confer their benefits under the conditions that occur in farmers' fields across the continent and around the world, not just in controlled conditions. Second, the number of plants that must be phenotyped is often in the tens or hundreds of thousands, both when uncovering the fundamental mechanisms of agronomically desirable phenotypes and when evaluating new varieties for release to farmers. Of course, greenhouse studies are and will remain important in plant sciences. Nonetheless, the vast majority of agricultural production is outside, in varying soil and changing climatic conditions, and under diverse management practices. Thus, researchers move their attention to phenotyping large numbers of plants in the field. Therefore, as part of this research, we built robotic platforms that can collect multi-modal, multi-character data in real time in the field [5]. The two robotic platforms developed for field phenotyping proved to be accurate, reliable, and highly correlated to manually extracted phenotypes, while also providing richer information – e.g. 4D models (3D+temperature) of the plants with a virtually unlimited number of traits that can now be extracted and correlated to plant responses. The large amount of data already collected will now help us to link plant genotypes as well as the molecular and eco-physiological responses with the expression of specific phenotypes in response to the growing conditions [6–8].

In this paper, we present a simulated environment for robotic phenotyping in the field. While real robotic platforms can operate and collect data under unforeseen situations, a simulation environment opens the door to further development of robotics and computer vision algorithms without some of the constraints of a real deployment. In that sense, the main advantages of a simulated environment are:

1) extended control over environmental and field conditions while easily creating various scenarios for testing the robotic platforms;
2) freeing the developers from limitations such as seasonal and weather conditions, type of crops, etc;

(a) Vinobot

(b) Vinoculer

Figure 1: *The developed platforms for high-throughput phenotyping in the field deployed at the Bradford Research Facility: (a) ground vehicle, Vinobot; and (b) observation tower, Vinoculer shown at the height of 15ft*

3) explore potential improvements in the current system architecture and design of the robots, by being able to add new elements without financial constraints;
4) availability of ground truth;

The remaining of the paper is organized as follows: in section II, an introduction to our real robotic platforms with a brief description of their different elements is presented. Section III focuses on the simulated environment and the challenges in mimicking real world scenarios, including the actual robotic platforms and the specifics of a corn field. In Section IV, we discuss the results obtained from running publicly available robotic and computer vision algorithms on the the proposed simulator and comparing the results of the same algorithms in the real world. Finally, in section V, the conclusions and future work are presented.

II. The Real-World Platforms

As introduced in [5], our system architecture consists of two robots: a mobile observation tower, *Vinoculer*, for canopy characterization and general inspection of the crop; and a ground vehicle, *Vinobot*, for individual and detailed plant phenotyping.

Figures 1a and 1b show the Vinobot and Vinoculer in a field at the University of Missouri Bradford Research Center near Columbia, Missouri, USA.

The ground vehicle, or Vinobot for ViGIR-Lab (Vision-Guided and Intelligent Robotics Lab) Phenotyping Robot, is responsible for phenotyping plants individually. In other words, the Vinobot moves within the field and collects data from individual plants, either on a regular schedule or by demand. The Vinobot consists of multiple sensors, such as for 3D imaging, temperature, humidity, light intensity (PAR), etc.. In the Vinobot, it is also included a differential GPS, a robotic arm, a LIDAR, and other support equipment for autonomous navigation and operation of the phenotyping sensors.

The second platform, Vinoculer, for ViGIR-Lab Phenotyping Trinocular Observer, is a portable and telescopic tower equipped with a 360-degree vision system that can observe a large area of the field using two (stereo) RGB cameras and one IR (thermal) camera. The main purpose of the Vinoculer is to detect regions of the crop under stress, and deploy the ground vehicle for further investigation of those regions.

III. Visualization and Simulation

The Gazebo software was used to simulate the robotic platforms as well as the corn field. Gazebo is an open source 3D simulator built on top of the Open-source Dynamics Engine (ODE) and the Open-source 3D Graphical Rendering Engine (OGRE) [9]. The software is fully integrated into the Robot Operating System (ROS) [10], which was also used in the real robots to perform navigation and data collection tasks. Our goal was to provide the same environment for both real and simulated robots, sensors, and actuators.

Similarly, a software named Rviz was employed for 3D visualization of not just the simulated robots (i.e their position, trajectory, etc), but also the data being provided to these robots. Like Gazebo, Rviz is integrated into ROS, but its main purpose is to visualize data collected by simulated **and** real robots. By doing so, the results from real and simulated robots can be correlated, making easy to debug the systems.

A. Simulated World

The first required element for the proposed system is the simulated *world*: in this case, a crop field. This simulated world consisted mostly of the plants and the ground soil – currently planar, but in the future, ground irregularities will be added. After that, the robotic platforms were added to the simulated *world* (field) so that navigation and data collection tasks could be performed. This simulation included the physics of the world, such as gravity, static and dynamic interaction between objects, friction, etc, as well as shadows and other illumination artifacts created by the sky, clouds and sun light.

Crop/Plants: In this paper, corn plants were considered as the specimen under study, however any other type of plant can be modeled and included in the simulation. The 3D models of corn plants were included as static rigid objects and the more typical non-rigid movement of plants was left for future work. As shown in figure 2, these 3D models were created with stalks, leaves, tassels, and ears. The field was randomly populated with corn at 10”$\pm$1” gaps, and placed along parallel rows, 30” apart. All parts of the plants were textured using real image templates.

Ground Soil: The ground was also modeled from textured templates of real soil with a Coulomb friction coefficient of $\mu_c = 50$ and second direction friction coefficient of $\mu_2 = 25$ (i.e. perpendicular to the first friction direction). These coefficients can be obtained empirically to match real-world conditions. The texture used for the entire ground plane was obtained from an image of an equal-size real field. Finally, the fact that the ground was made flat in this simulation

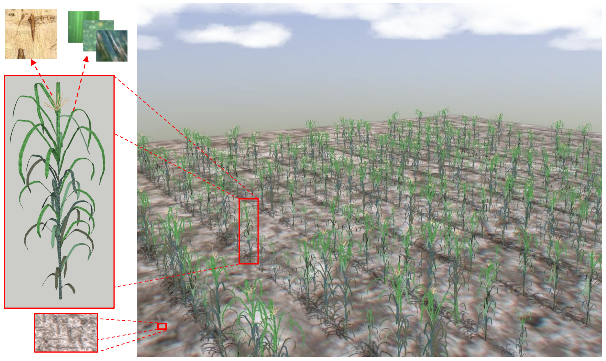


Figure 2: Simulated Field of Corn

does not compromise the results given that Vinobot is equally stable in the real field, which is a fairly flat terrain. However, simulation of a more rugged terrain was left for future work.

B. The Robots

The robotic platforms along with all their sensors and actuators were modeled identically to the real platforms. The only exception was for the thermal images which were not simulated in this work. As mentioned earlier, visualization and simulation of the robots was carried out using Rviz and Gazebo, respectively. Also, the algorithms for the simulated Vinobot and Vinoculer are identical to the algorithms used in the real robots, and they relied on the same ROS interface to send and receive command, observe sensory information, etc.

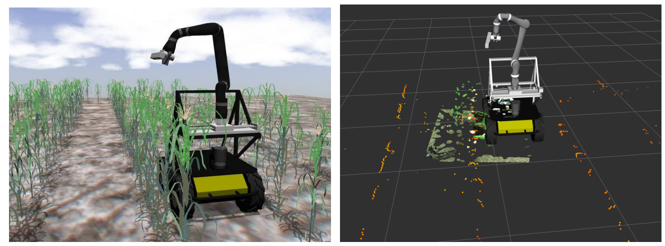
Vinobot: Vinobot was implemented around the Husky A–200 by Clearpath. A linear slide at the front of the robot guides a robotic arm ($JACO^2$ by Kinova) to improve lateral reach. The purpose of the robotic arm is to allow for multiple sensors to be handled. For example, the robot arm can move the camera – a BumbleBee XB3 by PtGray – in search of a better vantage point while 3D imaging the plants. Other sensors including a Differential GPS, an IMU and a LiDAR were also mounted onto Vinobot for navigation purposes.

In order to mimic real world conditions, appropriate noise was added to all sensor modules, i.e. the cameras, GPS, IMU, and LiDAR. A list of the all parameters used in the simulation are shown in Table I. These parameters were chosen from technical specifications and/or based on real sensor data. The reference latitude and longitude were set to the location of the Bradford Research Center in Columbia, MO, USA.

Figure 3a shows a screenshot of a simulation of Vinobot performed by Gazebo, while 3b presents a visualization of the real Vinobot by Rviz.

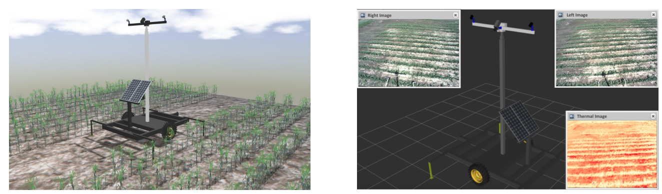
Vinoculer

Vinoculer is a portable observation tower usually mounted at the center of the field. It consists of a 360-degree turn table and it is capable of capturing data from a 30ft-radius surrounding area. The Vinoculer was equipped with two RGB-spectrum cameras for stereo vision (Grasshopper3 by PointGray), an IR camera (Flir A625) and a turntable with an accuracy of



(a) (b)

Figure 3: (a) Simulation of Vinobot in the field using Gazebo, and (b) Visualization of the real Vinobot and sensor data by Rviz. The orange points are parts of the plants detected by the LiDAR. The figure also displays the 3D point could being created by the stereo camera handled by the robotic arm.



(a) (b)

Figure 4: (a) Simulation of Vinoculer in the field using Gazebo, and (b) Visualization of the real Vinoculer in the field. Real RGB and thermal images are shown in detail.

0.1 degree. The cameras are necessary to perform measurements such as volume, leaf area, biomass, height, growth rate and other canopy characteristics (IR). These equipment were mounted on a telescopic tower, which can be elevated from 3 m to 10 m high. The base of tower has wheels, which allow its easy dislocation to any part of the field.

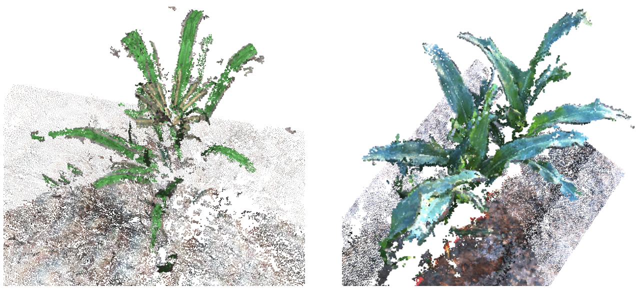
Figure 4a shows a screenshot of the Gazebo simulation of Vinoculer, while the Rviz visualization of the real Vinoculer is in Figure 4b. The height of Vinoucler can be set in simulation to range of 3 to 10 meters. The actual simulation of thermal camera requires modifications in physics of Gazebo therefore, here we treat the thermal camera as a gray-scale camera to detect objects of interest with emission and color property set to pure red color $[255, 0, 0]$. All cameras are simulated with the same resolution and frame rate as the real cameras (RGB: 4240×2824, 7 FPS – thermal: 640×480, 50 FPS). The turn table can be controlled through ROS service in the same way as the real platform.

IV. Results: From Real to Simulated Platforms

In this section, qualitative results using the real and the simulated platforms are presented. Two types of tests were carried out: 1) 3D imaging performed by Vinobot and Vinoculer; and 2) navigation and mapping performed by the Vinobot.

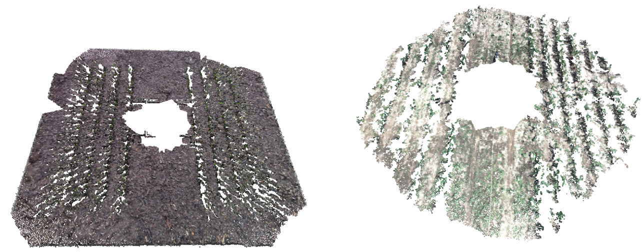
Table I: Parameters considered in simulation of sensors mounted on Vinobot

GPS	IMU	Camera	LiDAR
$refLat = 38.8°$	$accGaussN = 0.086(m/s^2)$	$stddev = 0.007$	$gaussN = 0.012(m)$
$refLong = -92.2°$	$rateGaussN = 0.86(m/s)$	$f = 1035,\ C = [663, 476]$	
$gaussN = [0.1\ 0.1\ 0.1]\ (m)$	$yawGaussN = 0.09(rad)$	$dist = [-0.35, 0.14, 0, 0, 0]$	



(a) (b)

Figure 5: Visual comparison between the 3D reconstruction of a corn plant generated using (a) synthetic (Vinobot collecting data in Gazebo) and (b) real (Vinobot collecting data in real world) data.



(a) (b)

Figure 6: Results for the 3D reconstruction of the entire field by Vinoculer using (a) simulated and (b) real data

A. 3D Imaging

An implementation of the algorithm for Structure From Motion name VisualSFM [11] was used to create the reconstructed dense models presented here. As mentioned earlier, these dense models were obtained from both real and simulated environments.

Vinobot: In this section, stereo images were used to create 3D models of individual plants. Figure 5 provides a visual comparison between the 3D models generated using synthetic and real data. By adjusting the noise added to the simulated cameras, we were able to reproduce the same "gaps" present in the 3D model from real plants. This is illustrated by Figures 5a and 5b.

Vinoculer: Even though Vinoculer cannot provide information at the same level of detailed and accuracy as from Vinobot, canopy traits like height, volume and Leaf Area Index (LAI) can still be extracted from the 3D images generated by Vinoculer.

As before, Figure 6 illustrates the results for the 3D reconstruction of the field using simulated and real data. In the simulation experiment (Figure 6a), the height of Vinoculer was set to its minimum, i.e. 3 meters, and the plants were modeled as in their early stage of growth (maximum height of $0.5m$). This was done to match the same conditions observed in one of the sets of the real data. The center of the 3D images in Figures 6a and 6b appear empty due to bottom of the camera viewing angle being aligned with the vertical, and hence the platform and its immediate surroundings cannot be seen by the cameras.

B. Navigation

Autonomous navigation refers to the ability of a robot to move within its habitat without human intervention. In order to achieve that, localization, mapping, obstacle avoidance and motion control algorithms are required to accurately control the robot's position in the environment (field) and to compute the path through obstacles (plants). Field navigation is a quite difficult type of navigation referred to as outdoor navigation in unstructured environment [12]. Illumination, non-rigid objects, dynamic scenes, and sensor noises are some of the challenges when dealing with outdoor navigation of robots. Besides, the requirement to localize the robot within one centimeter with respect to the plants adds another level to the complexity of these challenges.

Autonomous navigation using Global Navigation Satellite Systems (GNSS), e.g. differential GPS, is frequently used to mitigate some of these challenges. However, vision-based guidance is getting more attention as it can potentially reduce costs, handle dynamic situations and simplify installation, while it can achieve precision comparable or even better than from GNSS. In that sense, new algorithms for either 2D or 3D dynamic navigation relying on sensors such as LiDAR and RGB cameras can indeed provide increased flexibility in such a unpredictable environment [13–15].

In this paper, we propose the use of GPS, IMU, and LiDAR data to simultaneously localize the robot and map the environment (field). These sensory informations were fused using extended Kalman Filter (EKF) and the GMapping approach [16, 17]. The EKF component of our method relied on a publicly available implementation [18] where wheel odometry, IMU, and GPS data were fused to generate an estimate pose of the robot. This estimate is refined by another publicly available algorithm on OpenSLAM. The latter is an improved implementation of the Rao-Blackwellized particle filter for simultaneous localization and mapping. Here, LiDAR data along with the EKF estimate are used to refine the pose of robot while a map of the environment is created.

A manual navigation was employed with the goal of keeping

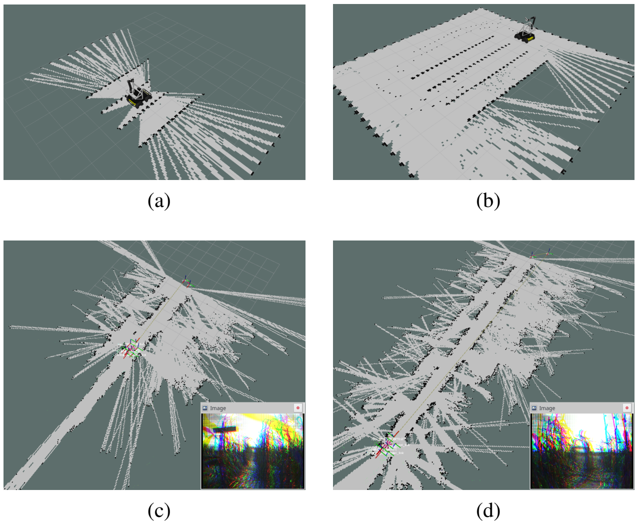


Figure 7: Visualization of Vinobot in Rviz while localizing itself and mapping the environments in (a, b) Gazebo simulation, and (c, d) real world using LiDAR, IMU, and GPS sensors.

track of the pose of Vinobot and to simultaneously map the rows of plants. Figures 7a to 7d compare the results of this experiment under simulated and real conditions. In the future, the obtained occupancy map will be used to autonomously navigate Vinobot through the rows while avoiding obstacles (plants).

V. Conclusions and Future work

In this paper, a simulation of previously developed architecture for plant phenotyping has been presented. The architecture consists of two robotic platforms: an autonomous ground vehicle (Vinobot) and a mobile observation tower (Vinoculer). While real robotic platforms can operate and collect data throughout the growing season, the simulation environment opens the door for further development of robotics and computer vision algorithms throughout the year. Another advantage of proposed simulation is to develop new ideas without confining to physical limitations like having multiple robots. The phenotyping platforms as well as the corn field were simulated almost identical to the real world conditions with uncertainties and noises. Results showed similar qualitative figures between the simulated and real platforms where same computer vision and robotics algorithms applied. We left some improvements including non-rigid simulation of plants, and simulation of non-plane terrain ground as future work.

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