Demo Abstract: Containerized Mobile Sensing Simulation Framework for Smart Agriculture

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ABSTRACT

We present a containerized mobile sensing simulation (CMOS) framework developed for smart agriculture applications. This framework includes 1) 3D environment and object modeling, 2) mobile platform motion planning and control, and 3) optical sensing simulation, all implemented and connected within containers. Specifically, we build a user-friendly interface for 3D modeling, *e.g.*, cornfield modeling using Blender. We use an unmanned aerial vehicle (UAV) as our mobile sensing platform and integrate UAV 3D model, flight path planning and control with robot operating system (ROS) packages and the Gazebo simulator. We also implemented optical sensing, *e.g.*, collecting RGB image data from cameras in our simulation framework. This framework can be used not only in leaf area index correction and other analytical support for agriculture operations, but also as a synthetic data annotation tool for leaf segmentation and other smart agriculture applications. We demonstrate the major components of the CMOS framework, and how to use it to automatically annotate image data for the leaf segmentation application.

CCS CONCEPTS

• **Computer systems organization → Robotic autonomy**.

KEYWORDS

Robotics, Mobile sensing, Simulation

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1 INTRODUCTION

Internet of things (IoT) and mobile sensing techniques play an important role in various smart agriculture applications. For example, unmanned aerial vehicles (UAVs) equipped with RGB and multi-spectral image sensors have been used to monitor crop growth for crop yield prediction purposes. Harvesting robots have been developed to detect and pick tomatoes with the help of camera and Lidar sensors. For these applications, complicated crop, terrain and other environment conditions need to be taken into consideration in order to provide analytical support for precision operations. For example, the leaf area index (LAI) derived from image sensors needs to be corrected due to the canopy overlap, and the LAI correction coefficient varies a lot for crops with different plant spacing. Thus, mobile sensing simulation becomes an important way to provide ground-truth and analytical information for smart agriculture operations, such as crop growth monitoring, etc.

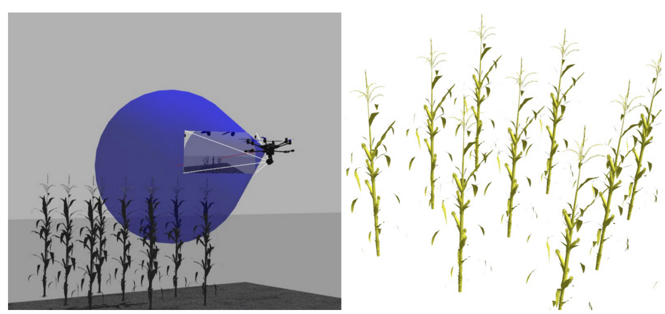

Figure 1: Simulation of UAV collecting corn image data in Gazebo (left); Annotated corn leaves and stalks (right).

Meanwhile, more and more deep learning algorithms have been applied to agriculture applications, such as crop detection, leaf segmentation, etc. However, a large number of annotated data is needed for developing advanced deep learning models, in addition to raw sensor data and algorithms. To obtain large scale annotated datasets for data hungry deep learning techniques, synthetic data has been used for aiding image segmentation and scene understanding problems in self-driving applications [3]. To generate synthetic data, various 3D modeling tools and simulators have been developed to perform data annotation automatically for self-driving research. Among them, open source simulators like the CARLA simulator become widely used due to their support for training and validation of autonomous driving systems, as well as their protocols and digital assets, such as buildings, vehicles, etc [2]. However, we are unaware of any open-source simulator particularly designed for mobile sensing in smart agriculture applications.

To fill the gap, we develop a containerized mobile sensing (CMOS) simulation framework, which is convenient for users to configure and deploy, and which provides digital assets for agriculture applications. Specifically, we build a 3D crop environment model with stalks of corn as an example in Blender. We use robot operating system (ROS), MAVLINK, PX4 flight control and other open source packages [1] to simulate and control UAV in the Gazebo simulation environment. We also develop optical sensing capability, *e.g.*, camera, Lidar sensor data simulation in our framework. Note that an interface between the 3D software Blender and the simulation software Gazebo has been developed and integrated in this framework to provide a powerful and user-friendly 3D model editing functionality. All the software components mentioned above are configured and composed in a single Docker image. In addition to the CMOS framework, we also demonstrate how to use our framework to perform synthetic data generation and annotation for deep learning-based image segmentation problems.

To summarize, we develop a user-friendly, out-of-the-box mobile sensing simulation framework for smart agriculture applications. We demonstrate how to perform synthetic data generation and annotation automatically with this framework. Note that once we complete synthetic data annotation in CMOS, it is straightforward to use the ground-truth data to calculate LAI correction coefficients for different plant spacing. We can also use the synthetic dataset for leaf segmentation and other applications.

2 FRAMEWORK DESIGN

The CMOS framework has three main components: 1) 3D environment and object modeling, 2) mobile platform motion planning and control, and 3) optical sensing simulation.

3D modeling: For agriculture applications, 3D models of various types of crops and terrains are needed. In the CMOS framework, we develop an interface for connecting Blender, one of the most popular 3D design software, with Gazebo, a 3D dynamic simulator widely used in robotic simulations. Since we perform mobile control, planning and sensing simulation in the Gazebo simulator, all models, *e.g.*, environment and vehicle models, will be imported and used in Gazebo. However, Gazebo is developed for robotic applications, which is not user-friendly for 3D object and environment design and modeling. Thus, a 3D modeling interface to Gazebo is developed. In this demo, we use the open source Blender software to design a cornfield with stalks of corn models and a flat terrain model. The user-designed 3D models in Blender can be automatically imported to Gazebo with our framework.

Mobile platform motion planning and control: While many motion planning and control packages are available in ROS, we choose to use PX4 [1] as our flight control toolset, and develop our own UAV flight path planning package. In this way, different types of UAV models are compatible with our framework, e.g., quadcopter, fixed-wing planes, etc. Users can choose mobile sensing platforms based on their specific needs and use case scenarios. Besides, both automatic and manual UAV flight controls are implemented using the PX4 stack. We use MAVSDK, a collection of libraries to interface with MAVLINK, to automatically send on-board and off-board control commands to UAV. We can also use the QGroundControl (QGC) software, which provides a GUI interface for users to manually define waypoints for any MAVLINK-enabled UAVs.

Optical sensing simulation: Optical sensors including monocular and stereo cameras, 2D and 3D Lidar, are simulated in our framework to produce various data streams. The 3D models of these sensors can be created and mounted on our mobile sensing models by designing and inserting SDF models of these sensors into the UAV models. Meanwhile, the PX4 ecosystem provides an interface to customize the position of the sensors mounted on vehicles in three degrees-of-freedoms (pitch, yaw, and roll) at runtime.

In addition to the open source CMOS framework discussed above [1], we also provide an example to show how to use this framework to generate and annotate synthetic data for the data-driven image segmentation application. Since the object texture and the collision model of the 3D models can be modified in the framework, we modify the collision model of the 3D models, to automatically annotate collected sensor data. For example, we assign different numerical values in the collision model to annotate different parts of the corn stalks, e.g., leaf areas. In addition, we include two modes of the 3D models: 1) a cornfield model with the corn natural texture and shadow effects turned on, 2) a 3D model with different values assigned to different parts of the corns, *e.g.*, leaves, stalks, etc., with the texture and shadow effects turned off. Since we can control the pose of the UAV and camera in simulation, an image dataset with all leaf areas annotated can be obtained from the 3D models with both RGB data and label information.

3 DEMO DESCRIPTION

Since all the framework components are composed in a single Dockerfile, in this demo, we first show how convenient it is to run the Docker scripts and deploy the CMOS framework on a Linux computer. Then, we take the cornfield monitoring as an example, and show how to configure and use our framework to automatically annotate the leaf areas of the corns captured by the camera in the simulation. We also demonstrate how we build a 3D cornfield model in Blender and how we integrate it to the Gazebo environment. More specifically, we choose the Yuneec hexarotor as our mobile sensing platform, a high-resolution 2D camera as our optical sensor. We set up a flight mission on QGC and use our PX4 packages to execute the mission to collect RGB image data from the two models mentioned above. As mentioned above, since one of the cornfield model mode contains the same labels for all leaf pixels, an annotated RGB image dataset for corn leaf segmentation can be generated, after matching the images captured from these two modes. Finally, a short demo video of using CMOS to collect cornfield RGB image data can be found here: https://youtu.be/B5zza7EkuaA.

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