PROJECT SUMMARY

Overview:

Title: Collaborative Research: NRI: StickBug – an Effective Co-Robot for Precision Pollination
PI: Yu Gu. Lead Institution: West Virginia University

The shortage of natural pollinators is threatening global food production, making it increasingly difficult to feed the ever-growing human population on Earth. Robotic pollinators can supplement insect pollinators to improve food security. They can provide additional services such as mapping and flower data collection. Robotic pollinators will also work in controlled environments not suitable for natural pollinators. To help realize these benefits, the objectives of this project are to 1) significantly improve the effectiveness and 2) lower the entry barrier of robotic pollination technology. The project aims to address several research challenges associated with precision robotic pollination: the spatial-temporal development of crops and flowers, the similarity of flowers in a cluster, the unstructured plants with occlusions, the large number of flowers needed to be pollinated, among others. To meet these challenges, the design of a six-armed precision robotic pollinator for greenhouse environments, StickBug, is proposed. Systematic field experiments are designed to evaluate StickBug's pollination effectiveness and its ability to work alongside human growers.

Keywords: Design, Human-Robot Interaction, Perception, Planning, Agriculture

Intellectual Merit:

1) The project integrates agriculture domain knowledge, custom robot design, robotics algorithms, and human systems methods to solve a complex real-world challenge. The complexity of the problem being tackled, i.e., large-scale manipulation of delicate flowers in diverse situations, is beyond most of the field robots in the past. 2) Knowledge and insights gained through this effort will advance robotics research in areas such as semantic mapping in dynamic environments, manipulation of deformable objects under occlusions, multi-arm task coordination, and tracking similar-looking objects under motions. 3) The emphasis on field testing and comprehensive evaluation of pollinator effectiveness will help close the gap between academic robotics research and the needs in real-world applications. 4) The development of algorithms to compensate uncertainties associated with using low-cost hardware components will help popularize low-cost robot's use in different applications. 5) The integration of human studies with the robot design and evaluation process will help make the robotic pollination technology acceptable to growers.

Broader Impacts:

1) With the aid of robotic pollinators, growers can overcome the shortage of natural pollinators to achieve improved productivity and obtain higher profit opportunities by planning flexible pollination schedules. 2) The pollination robot allows for selective pollination and better management of crops by timing and tracking pollinated flowers. 3) The ability for StickBug to manipulate delicate flowers in unstructured environments at a large scale will contribute to innovations in precision agriculture applications. 4) The project will create research and learning opportunities for undergraduate and graduate students from underrepresented groups, such as from socio-economically disadvantaged regions. 5) The open sharing of the proposed pollinator robot design, algorithms, and simulators would promote community collaborations. 6) The research activities will be integrated with workforce development to popularize robotics technologies in agriculture. 7) The project will promote outreach activities through the development of interactive robotic pollination demonstrations.

Requested funding agency: USDA/NIFA

Collaborative Research: NRI: StickBug – an Effective Co-Robot for Precision Pollination

1. Motivation

Feeding an ever-growing human population on Earth with deteriorating farmlands (Pan et al., 2016, Gray, 2019), a changing climate (Parry, 2019), and stressed ecosystems (Crist et al., 2017) is a formidable challenge for humanity. Within the delicately balanced food production process, insects, especially bees, play an important role in flower pollination. Without the pollinators, we would not be able to enjoy most tree fruits (e.g., apples, peaches), berries (e.g., strawberries, blackberries), melons, coffee, and more. Studies have shown that 87 out of 115 leading global food crops (Klein, 2007), and approximately one in three bites of our food (Buchmann & Nabhan, 2012), rely on pollinators. Globally, pollinators contribute to between $235 and $577 billion worth of annual food production (FAO, 2016).

This dependence on natural pollinators comes with risks and limitations. The global decline of bee population and diversity (Potts et al., 2016; Zattara & Aizen, 2020) has threatened agricultural production. Many farmers rent bees with growing costs (Sumner & Boriss, 2006; Lee et al., 2019). The increasing agriculture production in controlled environments (Benke & Tomkins, 2017) also presents challenges for bees, in settings that they either do not like or cannot survive.

Our *long-term goal* is to design robots that can take care of *individual* crops efficiently (i.e., phytotechnology; Blackmore, 2004). Like insects, future robots would provide *precision* services such as pollinating individual flowers *economically at a large scale*. Instead of developing these robots as bee replacements, we see them as a "plan-B" (i.e., for improved food security during insect declines), for supporting indoor agriculture, and for providing services beyond what insects can do, such as data collection. More specifically, the *objectives* of this proposed project are to 1) significantly *improve the effectiveness* and 2) *lower the entry barrier* of robotic pollination technology. The pollination effectiveness will be experimentally evaluated based on the flower pollination rate, quality of pollination, handling of difficult situations (e.g., occluded flowers), and system reliability in greenhouse environments. The effort on lowering of entry barriers will focus on developing robust algorithms to tackle the challenges associated with the use of low-cost components and the human-in-the-loop studies for improving the acceptance and usability of the technology by the growers. In addition, we recognize that the successful development, deployment, and popularization of robotic pollination technology would need significant community effort. Therefore, we strive to make our research open with the sharing of our hardware design, algorithms, software, simulation, and data sets.

2. Previous Relevant Work by Members of the Proposal Team

With a recently concluded project funded by USDA/NIFA under NRI, we developed a prototype robot for precision pollinating Bramble (e.g., blackberry) flowers in greenhouses. The fully autonomous robot, named BrambleBee (Fig.1), is able to map an unknown environment, identify flowers, estimate their poses, and perform precise manipulation of flowers for pollen transfer (Ohi et al., 2018; Strader et al., 2019; Yang et al., 2019; Mills et al., 2020). Our bee studies also helped understand their microstructure and movements for pollination (Park, 2017). BrambleBee received media mention by Wired, the Fruit Grower Magazine (cover story), Fast Company, TechXplore, Science, among others.

Fig.1. BrambleBee robot during an experiment at a West Virginia University (WVU) greenhouse.

During this past exploratory study, we have identified eight challenges associated with precision robotic pollination that would need further research to overcome:

1. Flowers do not bloom at the same time and each has a limited pollination window, making it important to track the spatial-temporal development of flowers over time.
2. The flower clusters, with multiple similar looking flowers overlapping each other, present significant perception and manipulation challenges (see Fig. 2 for an example).
3. The robot needs to be able to reach flowers that are tall, low, angled inward, or occluded (see Figs. 1 and 2).
4. There can be significant mobility difficulties for a wheeled robot to navigate around crops in close quarters, even in a semi-structured greenhouse environment.
5. The robotic pollination system needs to work alongside with and be easily accepted by growers.
6. The robotic pollinator needs to handle significant natural variations of flowers and be adaptable to different crops.
7. Pollination effectiveness, including success rate, throughput, and the quality of pollination, needs continued improvement to produce the quality and quantity of fruits comparable to insect pollination.
8. The overall system cost must be reduced, and reliability improved for robotic pollinators to become a practical component of agriculture systems.

Fig.2. Example of bramble flower clusters and occlusions that make robotic pollination a challenging problem.

If BrambleBee showed that precision robotic pollination is a technologically *feasible concept*, this project would demonstrate that it also can be a *practical solution*. In this proposed project, we aim to address Challenges 1 - 5 above and make significant progress on Challenges 6 - 8 through an innovative integration of hardware designs, algorithms, and human studies.

3. Background

3.1. Pollination

Pollination is a complex process that is vital for fruit development. Pollination occurs when pollen from the anther (male component) is placed on the stigma of a pistil (female component) of a flower. The pollen grains then germinate to produce pollen tubes containing two sperm nuclei. One of the sperm nuclei fuses with an egg to create an embryo, and the other nucleus mates with two polar nuclei to become an endosperm. An embryo, an endosperm, and a seed coat consist of a seed. The mating processes between sperm nuclei and nuclei of an egg is called fertilization. Once fertilization is completed, a fruit starts to develop (Acquaah, 2008). Thus, pollination is the first step of fruit development.

Currently, pollinators can be purchased or rented for field crop production during the flowering season. Field production allows natural pollinators to help with pollination. However, in controlled environment agriculture such as greenhouses, pollinators have to be artificially introduced. In greenhouse production, hives of bees are purchased and placed inside. If the lifespan of the bees is shorter than the flowering period, hives must be continually replaced (Petrovic, 2017). This continual replacement of pollinators adds additional cost and stress for growers to ensure that hives arrive on time. Additionally, in controlled environments, bees are not as active or efficient as they were in nature due to the relatively higher temperature and humidity. Bees also tend to escape from the greenhouse. Whittington et al. (2004)

evaluated the pollen collected by bumblebees in a greenhouse. Bees were released to pollinate tomatoes and were allowed to exit and return to their hive in the greenhouse. Depending on the time of year and availability of other plants, up to 73% of the pollen was from other plants than tomatoes. This study stressed that the bees were not necessarily pollinating only crops of the grower's choice. In addition, the bees are also treated as disposable commodities. The pollination activity only lasts for four to six weeks (Biobest, 2021). Once the pollination begins to decline, the hives harboring the queen bee need to be disposed of. The longevity of the hive is not expected to last beyond the pollination period and does not support the reproduction of the bees. Generally, the greenhouse environment is not ideal for bees (Goff, 2021), and an alternative method of pollination is desired.

3.2. Agriculture Robotics Research

High-value specialty crops are getting special treatments by robots. Working at the individual plant-scale, robots are being developed for planting (Srinivasan et al., 2016), inspection (Bengochea-Guevara et al., 2014), pruning (Botterill et al., 2017), selective irrigation/fertilization application (Thayer et al., 2018; Shivaprasad et al., 2014), phenotyping (Mueller-Sim et al., 2017; Young et al., 2019), pollination, fruit picking (Li et al., 2016; Zhang et al., 2016; Silwal et al., 2017; Xiong et al., 2020), among others (Vougioukas, 2019). This has become a new frontier for precision agriculture and an active playground for field roboticists.

Each plant is a unique living creature. For a robot to effectively interact with a part of the plant (e.g., branches/canes, leaves, flowers, fruits, etc.), it must overcome several challenges. First, the robots need to deal with the semi-structured environments and unstructured plants with significant natural variations (Bechar & Vigneault, 2016). Second, crops are often densely populated with occlusions. Third, plants are changing over time with both slow (e.g., growth) and fast movements (e.g., touched by growers or robots). Fourth, manipulating delicate living cells (e.g., flowers, fruits) requires carefully designed mechanisms and maneuvers. Finally, there would be many individual plants, and even more fruits and flowers, in an agriculture production system for the robots to handle.

Although very few agricultural robots focused on plant-scale applications have matured to the commercial production level yet, significant progress has been made by the community to overcome these challenges (Vougioukas, 2019). A commonly adopted approach is "structuralization"; i.e., transforming the production setting to fit automation goals. This is sometimes achieved through a co-design process (Bloch et al., 2018) that optimizes the field layout, crop training, and the robot design together as a system. This approach, however, makes the developed robot system more specialized (e.g., performing a particular task on a particular crop in a particular environment). A few systems also leverage human abilities to bypass some hard robotic tasks, such as delicate and dexterous manipulation for fruit picking (Lu et al., 2017).

In the long run, with improved autonomy, robots would become general-purpose grower assistants that can better deal with unstructured environments and complex situations. Precision robotic pollination that requires physically touching the flowers for pollen transfer is one area that could greatly benefit from these advancements. Compared to fruit picking, research on robotic pollination has been very limited. Several robotics researches used pollination as an aspirational, instead of a tangible goal (Binns, 2009; Wood et al., 2009; Berman et al., 2011). The few actual robotic pollination studies so far have involved non-precision approaches (Yang & Miyako, 2020), precision non-contact based pollination such as targeted spaying (Yuan et al., 2016; Williams et al., 2020), and precision contact based pollination (Shaneyfelt et al., 2013; Ohi et al., 2018, Strader et al., 2019) like actual insects would do. Making robots that can precisely detect, localize, and manipulate a large number of flowers in common agriculture settings is still a major engineering challenge.

Several underlying technologies needed for robotic pollination, such as mapping, object recognition, inspection, and path planning, are shared with robots developed for fruit picking and phenotyping applications (Sa et al., 2016; Vázquez-Arellano et al., 2016; Dias et al., 2018). The ability to sense, evaluate, and manipulate flexible objects, such as branches/canes, developed for robotic pruning research (Botterill, et al, 2017; He & Schupp, 2018; Zhang et al., 2019), may help robots to pollinate flowers in hard to reach places. In return, the specialized knowledge acquired through developing precision robotic pollinators, such as perception and fine manipulation of delicate flowers in cluttered environments, would contribute to the community for solving other agricultural robotics problems such as harvesting small berries.

3.3. Human-Robot Interaction (HRI) Challenges in the Agriculture Setting

While traditional agricultural robots are normally physically separated from humans working on other tasks, collaborative robots are designed to work alongside human co-workers. However, by putting robots into greenhouses or other agricultural settings, new safety hazards may be introduced (e.g., collision, excessive cognitive stress, etc.). If done indiscriminately, just because a robot can do a task, it does not always improve the job for the operator and in some cases can reduce productivity or increase physical and mental workload. However, with more than 50 studies in agricultural robotics research identified by Hajjaj and Sahari (2014, 2016), there is almost no mention of collaborative HRI frameworks that are specific to agriculture. The only study that was mentioned in the reviews is Kashiwazaki et al. (2010)'s cart style robot for greenhouse work. Another review by Vasconez et al. (2019), also portrait the same situation, with only one of the studies feature a collaborative robotics experiment (Oren et al., 2008).

The adoption of new technologies in agriculture is rarely immediate. Technology adoption is a complex activity and many factors influence these decision-making processes (Agarwal et al., 1999; Dimara et al., 2003). A rich body of the literature has confirmed the environmental and economic benefits derived from robotics and/or technology-based precision agriculture (Batte et al., 2003; Pierce et al., 2008). Nonetheless, a low rate of adoption is still observed by both academic surveys and professional reports (Ellis et al., 2010; Fountas et al., 2005) among precision agriculture industries. Some of the important aspects catalyzing the adoption of precision agriculture technologies include costs reduction (increasing profitability) (Hite et al., 2002; Adrian et al., 2005; Folorunso et al., 2008), and adopter's confidence in the technology (Aubert et al., 2012; Marra et al., 2010). Therefore, in this proposed project, we aim to lower the entry barriers by leveraging participatory design (Spinuzzi, 2005; Robertson & Simonsen, 2012) approach and user-centered theory (Johnson, 1998) to foster a higher adoption of the precision pollination robot.

4. Technical Approach

4.1. Crop Selection

Two horticulturally important crops, blackberry and tomato, have been selected for this project. Blackberries (*Rubus fruticosus*) are referred to as caneberries or brambles. Blackberry production has been increasing in the U.S. In 2017 the value of the crop was estimated at $31.1 million, which was up 4% from the previous years (USDA NASS, 2018)**.** The production increase was partially stimulated by the demand for fruits viewed as health-promoting crops. Brambles contain high vitamin C, folate, and anthocyanin contents (North American Raspberry and Blackberry Association, 2021). Thus, brambles are regarded as high-value crops providing health benefits from anticancer, antiviral, and antiallergenic properties for consumers and a high profit for growers (Hummer, 2010). Our second crop is tomato (*Solanum lycopersicum*), one of the top three vegetable crops produced in the U.S. The value of tomatoes grown in the U.S. in 2020 was $1.66 billion, a 4% increase from 2019 (USDA NASS, 2021).

While both crops are popular, increasing in consumption, and having potential health benefits, they have different pollination mechanisms. Blackberry flowers consist of hundreds of pistils and develop into druplets after pollination. The druplets are attached to a receptacle to form the core of the fruit. Because of the large number of pistils, it is not easy to pollinate all pistils. Bulk pollen transfer using a mechanical tool facilitates blackberry pollination. On the other hand, the tomato has a single pistil with anthers below it. Because the flower faces downward, the flower requires vibration (sonication) to pollinate the flower.

Blackberries are pollinated once a year in the spring and tomatoes in the greenhouse require 30-35 weeks long pollination per year (Goff, 2021). Both crops need pollinators for adequate fruit development. Through working with these two crops with very different pollination requirements, we are hoping to gain insights and experiences for adapting the robotic pollination technology to more crop types.

4.2. Overall System Design

4.2.1. Use case scenario

A typical application of the proposed precision pollination system is illustrated in Fig. 3. In this scenario, a robotic pollinator works alongside growers in a large greenhouse setting when the flowers are in need for pollination. The robot is responsible for the time-consuming tasks of flower inspection, mapping, pollination, and development tracking. The growers are mainly taking care of other greenhouse tasks (e.g., planting, irrigation, pest control) and providing support to the robot.

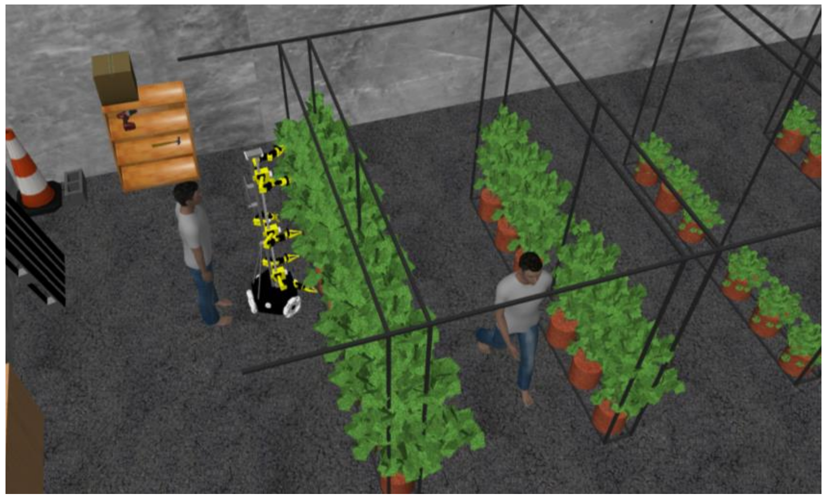

Fig. 3. Illustration of a grower checking on the work of a pollination robot in a simulated greenhouse environment. The robot height is about 2 meters.

The daily schedule of the robot pollinator starts from an inspection pass in the greenhouse, where it updates a semantic map and evaluates the spatial distribution of flowers and the pollination workload. Based on this map and with inputs from the growers, the robot's overall pollination route is planned. Along the route, the robot would stop in small increments (e.g., 60 cm, about one robot base width) if there are flowers to be pollinated. At each stop, it first creates a detailed 3D semantic map of the local workspace, including labeling of flowers and their poses, canes, and other relevant features. Using this map, the task for each of the robot's six arms are planned (e.g., for pollination or pushing aside a cane). The robot then pollinates all the reachable flowers in the local workspace before moving on to the next stop.

4.2.2. Precision pollination robot design

A preliminary design of the proposed robotic pollinator, StickBug, is shown in Fig. 4. The robot has a holonomic drive base that allows fine adjustments of the robot pose to fit in tight spaces for reaching flowers. The main structure on the drive base is a vertical lift made of a long lead screw and a support column. Three "elevator cabs" move up and down on the leadscrew and each of them carries a pair of robotic arms. The vertical lift allows the arms to have a large workspace along the robot *z*-axis, in order to reach flowers that are located high or low on a plant. For the prototype robot, each robotic arm will consist of five Dynamixel servos. The linear motion by the "elevator" that is shared by each pair of the left and right arms, along with the actuations of the end effectors contribute to additional Degrees of Freedom (DoF) for manipulation. The robot is designed to be inherently safe (Möller & Hansson, 2008) with low potential and kinetic energy (e.g., similar to human body mass but with a low center of gravity and slow max speed of 0.5 m/s), along with short and weak arms. Additionally, the robot will be equipped with emergency lights and E-stops, in addition to active recognition and warning of nearby people.

Exchangeable end effector designs (e.g., for flower pollination and for cane gripping) will be used on the arms, as illustrated in Figs. 4 and 5, to support different situations and task requirements. The pollination end effector (Fig. 5, left) would be a soft parallel manipulator (with a flexible center joint) that can provide three DoF motion: one translation (i.e., moving forward/backward) and two rotations (i.e., pitching up/down and yawing left/right). It can also generate orbital motions of the pollination tip for simulating bee's movements in a flower (Park 2017). The flower interface, i.e., the tip of the end effector, will be tailored for the type of crop to be pollinated. For example, dewaxed goose down, which was found in our previous study to be similar to the microstructure and mechanical quality of bee's hair for pollen gathering, would be used for bramble flower pollination. Alternatively, a vibrator, simulating bumblebee's motions, would be used for tomato flower pollination. Another end effector, a gripper, will have a compliant design and tactile/force feedback for grabbing canes. The design of StickBug leverages the vertical lift, the Dynamixel arm, and the gripper design from a robot we developed for the University Rover Challenge (Fig. 5, right). The pollination end effector designs will also evolve from the design made for BrambleBee (Fig. 5, left).

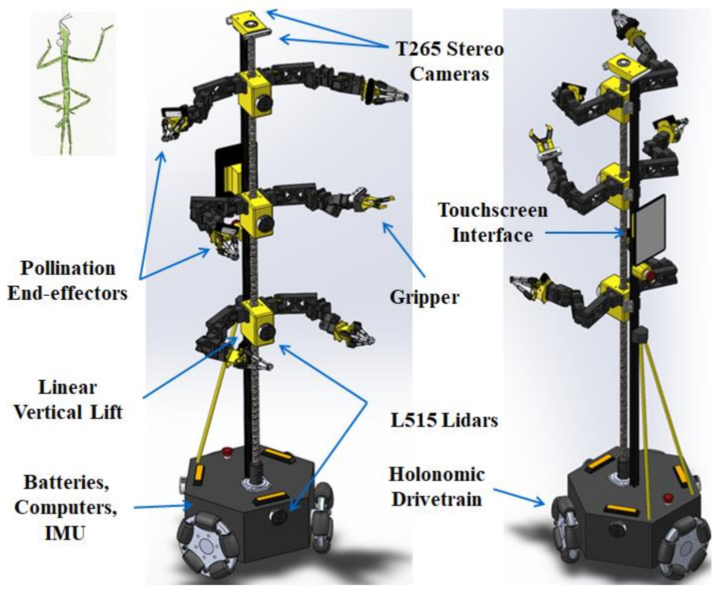

Fig. 4. Conceptual design of the proposed StickBug robot. Stick bug cartoon (top left corner): Chris Naylor-Ballesteros.

The robot sensors will include an Analog Devices iSensor Inertial Measurement Unit (IMU), three wheel encoders, two 170 degree field of view Intel Realsense T265 stereo cameras on top of the vertical lift (back to back and tilt down 30 degrees) for greenhouse mapping and human detection, and three Intel Realsense L515 Lidars on the robot base for obstacle avoidance. Additionally, a L515 Lidar will be mounted on the center of each of the "elevator". With vertical linear movements, these RGB-D sensors can quickly scan the pollination workspace in front of the robot and provide a detailed 3D map. They would also support real-time pose estimation for the low-cost manipulators, to be discussed in the "robot perception" section later. On each pollination end effector, a RGB camera will be used for guiding the pollinator motion, coupled with an IR proximity sensor to confirm the touching of a flower. On the end effector for gripping, an Intel Realsense D435 RGB-D camera will be used to help estimating the pose of canes and tactile sensors will be used for touch sensing. The sensor data will be fed to and shared by two onboard computers on a local network, one dedicated for robot perception and another one for planning and control. The robot will be powered by Li-Fe batteries through a custom power management system designed at WVU. The large battery packs will ensure continuous operation of the robot for over four hours between automatic charges or the manual change of battery packs by a grower. Two practical challenges associated with this robot design are expected to be the cable management of a six-armed robot and the calibration of extrinsic parameters of cameras mounted on the low-cost and less-precise robotics arms. The latter will be discussed further in the next section.

The human grower support includes overseeing the robot's work, making high-level decisions, providing performance feedback, reporting issues, performing routine maintenance, and occasional troubleshooting. The robot will communicate to the growers' phones with a local Wi-Fi network. Using the phone, a grower can monitor the robot's activity (e.g., real-time pollination statistics), see its plans, and provide inputs to the robot. The same information is also displayed on the touch screen carried on the back of the robot.

The design of StickBug builds upon lessons learned with BrambleBee. StickBug design addresses the mobility and control challenges around crops with a holonomic drive base, supports faster pollination (with six manipulators) and a larger workspace (with the vertical lift), allows handling of more complex situations (e.g., cane moving) and improved human-robot collaboration. StickBug is also expected to cost four times less than BrambleBee at approximately $25k for the prototype. The use of low-cost components in the StickBug design creates several robot perception and decision-making challenges, which will be discussed in the sections below. In parallel with the physical robot development, we will also update our recently released robotic pollination simulation (WVU Robotics, 2021) with the StickBug design (an example was showing earlier in Fig. 3) to support software development and integration.

Fig. 5. (left) soft parallel end effector designed for BrambleBee pollination; (right) the linear vertical lift, Dynamixel servo based manipulator, and compliant gripper developed by the PI's student competition team.

4.3. Robot Perception

4.3.1. Localization and greenhouse semantic mapping

Global mapping will consist of a Dynamic Scene Graph (DSG, Rosinol et al., 2020a) with three levels, 1) overall greenhouse, 2) individual pollination workspaces, and 3) underlying mesh, to inform the decision making of both the robot and humans working in the greenhouse. The top level of the DSG will consist of the entire greenhouse room and its overall structure and layout. This layer will be initialized using a prior map of the room with semantic labels associated with items such as: wall, floor, table, crop row, etc. It will be populated with sub-maps that each represent a local pollination workspace location. Metadata about each workspace, such as, the number of flowers, percentage pollinated, and percentage ready for pollination will be stored and globally referenced to inform robot motion planning. Further, humans and other likely dynamic objects that move throughout the top layer of the DSG will be identified and marked as dynamic so as not to impact the map following an approach such as (Scona et al., 2018). Additional objects such as tools placed by human growers will also be identified as dynamic objects for the same reason. Next, within a specific local workspace location, the second level in the DSG, will consist of a semantically labeled 3D map. This layer will be presented in more detail in the next subsection. Finally, the bottom layer within the DSG will consist of the underlying metric-semantic mesh constructed from stereo-Visual-Inertial Odometry (VIO).

For each robot, the baseline localization approach for navigating of the top level of the DSG will consist of stereo-VIO using the two Intel Realsense T265 stereo cameras mounted on the top of the robot. Our stereo-VIO and mapping implementation will build upon the solution offered by the open-source Kimera VIO navigation stack (Rosinol et al., 2020b). In particular, to increase the level of precision and robustness, additional localization constraints from wheel odometry and robot dynamics (Kilic et al., 2021) will be integrated into the back-end factor graph. The semantic image labels will be determined using a package such as Ultralytics open-source yolov5, and the Kimera-Semantics module (Rosinol, 2020b) will be used to annotate the 3D metric mesh from 2D pixel-wise labels.

4.3.2. Pollination workspace semantically labeled mapping

For each pollination workspace location, a high-fidelity map will be estimated to support pollination planning and execution. To facilitate global planning, a summary of each workspace will be extracted for representation in the top layer (e.g., number of flowers in the workspace, percentage of pollinated flowers, number of buds that will soon become flowers). To estimate a semantically labeled map of a workspace, the primary input data will be the three L515 Lidar-cameras on the center of the robot manipulator lifts. To support faster mapping of the workspace and reduce the potential for flower occlusion, we will use the vertical lifts to move three RGB-D sensors to generate an independent 3D map with each sensor. The three maps will then be merged considering their overlapping regions (Li et al., 2019, Bonanni, et al., 2017) and using the accurate position measurements along the vertical lift. Once a merged 3D map is created, just as in the greenhouse map, an object identification classifier, trained with a human-labeled data set, will distinguish between different image classes including: flowers (with assessment of its readiness for pollination), leaves, canes, and permanent greenhouse structure in the map. These 2D labels will then be used to annotate the 3D map given their known correspondences. This perception technology is readily available with existing open-source tools; however, we propose to address several important challenges that are widely applicable to low-cost precision agriculture robotics.

One challenge will be to estimate the deformability and therefore maneuverability of the plants in the map to inform planning hard to reach flowers. As a baseline, we plan to empirically estimate a functional relationship between cane sizes/shape and deformability and then refine this model over time during operation. In particular, we will use (Huang et al., 2013) to extract the skeletal structure of the plant, including topology (e.g., branching) and cane lengths and diameters. Using a force sensor on the robotic grabbing end effector, a series of tests will be conducted with input force and amount of deformation are varied for several different canes while grabbed at different locations. A Gaussian Process Regression (GPR) will then estimate a baseline functional relationship.

Another important challenge that must be overcome when pollinating a specific plant is the spatial-temporal changes of the pollination workspace. For example, moving a cane to reach a flower would likely cause labeled and mapped flower clusters to shift, with some flowers to be occluded and others appearing as new. To handle data association under a highly dynamic condition, we plan to leverage the relatively fast update rate of the L515s (30 fps) to represent the plant as a Truncated Signed Distance Field (TSDF) using a solution such as DynamicFusion (Newcombe et al., 2015). To handle the challenges associated with slower motion, such as natural growth and the uncertainties due to sensor noise, we will represent each cluster as a graph, with the vertices being flower centers. Using the graph of a cluster to extract the topology, taking inspiration from (Chebrolu et al., 2020), we will implement a hidden Markov model to determine flower correspondences before and after an event and to account for missing correspondences or new flowers arising. Once correspondences are established, the relative transformations for each flower with respect to its prior location in the map will be estimated to inform pollination planning.

4.3.3. Flower pose estimation and active perception

For the task of flower pose estimation and pollination, an operational challenge that must be overcome is the extrinsic calibration between the cameras used for workspace mapping and the cameras on end effectors. For example, with our low-cost robotic arms, we would not have reliable transformations from servo feedback to associate eye-in-hand cameras with the depth cameras (i.e., three L515) mounted on the robot. To address this, when visible in an L515, the poses of the end effectors will be estimated using a set of Kalman filters using observations from markers included on each end effector. Likewise, for an initial calibration before operational use, a calibration marker will be placed above each L515 such that each end-effector camera can look back and resolve its extrinsic calibration.

The BrambleBee's flower detection and pose estimation software leveraged a segmented point cloud of the flower from an RDG-D sensor to estimate flower pose using principal component analysis. In the proposed StickBug robot, we seek to perform flower pose estimation using only RGB cameras, in an effort to reduce cost (i.e., data throughput, computation). We propose to leverage recent developments in monocular RGB object pose estimation for manipulation tasks such as PoseCNN (Xiang et al., 2017) and SilohNet (Billings et al., 2019) for our problem given proper object segmentation and training. Active perception will be employed to reduce flower pose uncertainty during a pollination sequence and account for uncertainty in the state transition model. In particular, we will empirically determine the uncertainty of the pose estimator as a function of relative geometry through controlled tests (e.g., using a flower model at several known poses). This will enable us to determine the direction of the motion that can reduce pose covariance to be integrated in the motion planner's cost function later.

4.4. Robot Decision Making and Planning

4.4.1. Robot drive planning

StickBug's drive planning includes the planning of the initial inspection path for creating/updating the DSG, the planning of a pollination route and a sequence of poses along the route for the robot to stop and pollinate flowers, as well as the motion planning for reaching desired goal poses while avoiding obstacles along the way. The planning of both the inspection and the pollination paths can be considered as solving different variations of Vehicle Routing Problems (VRP) and will be built upon our previous work on pollination route planning (Tatsch, 2020).

Based on the prior map of the greenhouse environment, a graph is first built to represent topological relationships of different points of interest within the greenhouse. The inspection path will be first solved using the Google Operations Research (OR) tools (van Omme et al., 2014). This initial path will be modified online during the DSG map creating/updating process to drive down local uncertainties in the map using an information-theoretic approach (Bircher et al., 2016). Occasional replanning using the OR-tools may be needed when an edge (e.g., a corresponded crop row) is found to be blocked.

The pollination route planning will be modeled as a VRP with Time Windows (VRPTW) problem (Cordeau et al., 2000). Compared to the inspection path planning problem earlier, there are several differences here. First, the topological graph (i.e., the roadmap) will be expanded so that the robot can visit both sides of the crop rows in close proximity (Tatsch, 2020). The pollination stopping poses would be predetermined so that the mapping of each workspace can correspond to the previous data in the DSG. Note that not all stopping poses need to be selected by the pollination route. Second, the value of each edge would incorporate the estimated number of flowers to be pollinated along this segment, using the information provided by the DSG. Third, the robot may not be able to complete a full pollination pass of a large greenhouse in one day so decisions must be made on which areas would be prioritized. Finally, flower viability (e.g., flowers in areas not pollinated during the previous day may need additional attention) and growers' schedule (e.g., blocking off certain rows for other work) need to be considered in the planning. Two layers of optimization will be used to solve the pollination route planning problem. In a higher layer the complete route, including multiple days if necessary, is calculated before each pollination day considering a static average cost to complete each of the tasks. Based on this rough plan, a lower layer optimizer then considers higher-fidelity cost estimates, time constraints, and additional requirements. The Guided Local Search (Kilby et al., 1999) meta-heuristic will be applied in both layers with different sets of constraints.

With a holonomic drive base, robot motion planning can be modeled as a Partially Observable Markov Decision Process (POMDP) on an occupancy grid. The robot maintains an egocentric local occupancy grid map that encodes the obstacle probability for each cell (e.g., some plant parts may be deformable). With an efficient QMDP planner based on our previous work (Nguyen, 2020), the robot can plan a motion toward the goal pose while avoiding obstacles along the way.

4.4.2. Multi-arm cooperative task and motion planning for efficient pollination

The task of coordinating six robotic arms may seem daunting at first. Therefore, a key research effort here is to find innovative ways of breaking down and simplifying this complex problem to be solvable with available tools. The first opportunity of simplification is related to the mostly independent nature of the arms' tasks. For example, each arm would be responsible for either pollinating a different flower, moving a cane out of the way, or helping another arm to complete its task by providing a better camera viewpoint. The manipulation would also not involve a closed kinematic chain. For example, if a cane needs to be moved, pollination actions would be performed only *after* the crop stops moving. Therefore, the multi-arm planning problem can be largely viewed as a heterogeneous multi-agent system problem (Schillinger et al., 2018) with collision constraints.

Based on the semantic map and the flower poses, each flower will be classified as *directly reachable*, *indirectly reachable* (i.e., needs the help of cane moving), and *not reachable*. First, heuristics will be developed to assign flowers to the left or right-side arms and the flowers clearly not reachable (e.g., facing inward) would be labeled. The reachability of the remaining flowers will be analyzed through trajectory planning (Holmes et al., 2020). More specifically, starting from a collision free (for the end effector) plan produced with RRT* (Karaman & Frazzoli, 2011), Autonomous Reachability-based Manipulator Trajectory Design (ARMTD, Holmes et al., 2020) computes a reachable set of the full arm and performs trajectory optimization. The directly reachable flowers are the ones that the planner would successfully report a solution while the indirectly reachable flowers are the ones with a cane as the only obstacle that could be in collision (contacting with a leaf would be ignored). This trajectory planning process will also estimate each flower's manipulation cost to support task planning later.

For pollinating directly reachable flowers, the task assignment (e.g., which end effector for which flower) will be based on the reachability analysis above with task sequences planned using Planning Domain Description Language (PDDL, McDermott et al., 1998). Task planning will consider simultaneous pollination actions of multiple arms. Adequate vertical separation between robotics arms will also be included as constraints to reduce self-collision. Motion planning will again be performed using ARMTD with the consideration of redundant DOF in the end effectors and the sharing of the vertical base motion between each pair of left and right arms. Motion planning also facilitates the reduction of flower pose estimation uncertainty and ambiguity of the flower association within tight clusters; i.e., active perception as discussed earlier in subsection 4.3.3.

For the indirectly reachable flowers, the pollination planning process is more challenging, as it involves the cooperation of multiple manipulators. For example, one arm moves a cane aside, with the camera on another arm keeping an eye on the flowers of interest (i.e., viewpoint planning), and a third arm then performs the pollination actions. To simplify the problem, we will focus on pollinating one flower at a time during this stage. This is an integrated task and motion planning problem with spatial-temporal constraints. We propose to solve this challenging problem with the following steps. For the flower of interest, a reachability analysis (similar to the discussion earlier) is first performed to determine which cane needs to be moved. The canes would be modeled as deformable one-dimensional objects (Javdani et al., 2011). A clean segment on a cane near the flower of interest is then chosen for grasping (Langsfeld et al., 2017). Next, integrated task and motion planning are performed using a sampling-based approach (Garrett et al., 2018, 2020). This determines, for example, a new cane pose to be moved to and a camera viewpoint for monitoring the process, and plans the manipulator motions to complete these tasks. Due to the minimum forces required for flower pollination and cane moving, the manipulator force control is not needed in this application. The tactile sensors on the end effectors are used for contact/grasp confirmation and the manipulator joint torque feedback are used for anomaly detection (e.g., touching a non-deformable object).

4.5. Human-Robot Collaboration

A series of human subject experiments will be conducted throughout the project. The main objective of these experiments is twofold: 1) exploring the health and safety implications of greenhouse workers collaboratively working with the StickBug. Findings will be deployed as design guidelines on our robot development to improve the HRI performance; 2) investigating key facilitators and barriers that influence professional greenhouse growers from adopting robotics approaches in their tasks. Subsequently, we will develop low-barrier smart-phone based user interfaces to improve the usefulness of the HRI information presented.

4.5.1. Hierarchical task analysis for physical and cognitive load evaluation

We will develop a Hierarchical Task Analysis (HTA) (Stanton, 2006) for the protocols used by the greenhouse growers for different routine greenhouse activities without the introduction of the robot (i.e., standard operating procedure). In particular, we will investigate how they work with/out bees, and how this human-bee co-populated environment impacts growers' productivity, situational perception, and safety. The HTA will provide a baseline for evaluating cognitive task load of the growers and the overall human-robot teaming productivity as a result of deploying the pollination robot.

There is limited theoretical development on the relationship between greenhouse growers (or a broader scope – the agriculture workforce) and robotics adoption, and there is a need for technology acceptance studies to investigate further beyond simply describing barriers and facilitators to co-robot technologies. Technology Acceptance Model (TAM) and Unified Theory and Acceptance and Use of Technology (UTAUT) are two gold standard methods often referred to when investigating technology adoption (Davis, 1989; Venkatesh et al., 2003) and will be applied in the study. Focus group interviews will be conducted during this task in which 6-8 greenhouse growers will be recruited per round (3-4 rounds of interviews will be conducted). Participants will be introduced to a variety of greenhouse co-robot applications (pollinating, pesticide application, etc.) through formal presentations. Participants will be asked to rate the technologies on factors such as perceived value to operations, effort to learn and use, need for and availability of assistance in occupational safety, and privacy concerns. Subsequently, TAM and UTAUT models predict operator attitudes towards robotics technology adoption will be developed in terms of the significant factors revealed by the focus group investigation. Outcomes from this research activity will also be used to identify the preferable combination of technologies for specific greenhouse operation processes, to help lower adoption barriers, and to assist in defining and programing appropriate interaction behaviors between human growers and robots.

4.5.2. Collaborative robotics design evaluation

Each major pollination robot function module that might influence the surrounding growers' safety or work performance will be evaluated internally by engineers first, then professional growers. The user experience for each robotics interface function cluster will be assessed by the Questionnaire for User Interaction Satisfaction (QUIS) (Chin et al., 1988). The usability will be assessed using the System Usability Scale (Bangor et al., 2008). There will be scenario-based studies designed to evaluate the usability, user experience, stress levels, and cognitive task loads associated with different interface designs. Co-PI Hu has training and experience in the use of physiological measures in human-systems projects (Hu et al., 2016; Hu et al., 2018; Lu et al., 2021). Physiological metrics will be utilized to measure stress levels of the greenhouse growers during experiments and training scenarios, and results would be summarized as guidelines for the next iteration of design modifications. In addition, subjective surveys such as the NASA-TLX survey (Hart et al., 1988), Cognitive Task Load (CTL) method (Choi et al., 2014) and cognitive task analysis (Schraagen et al., 2000) will be evaluated.

The initial phase of this task will be the adaptation and enhancement of existing User Interface (UI) developed for robots at WVU. In this project, smartphone based Graphic UIs (Stone et al., 2005) will be designed and customized for the general preferences of greenhouse growers and environment contexts through an iterative process. Even though more advanced wearable technologies are emerging (e.g., Hololens), we decide to pursue a smartphone-based solution due to its low cost and wide adoption, which could contribute to lowering the potential users' entry barrier. This smartphone interface will include essential function clusters, including video streaming from the robot, the semantic mapping information, planned pollination route, as well as some robot's key performance indicators (e.g., total number of flowers detected, density, percentage pollinated, failure rate, etc.). In addition, the interface would also support some user-initiated safety-oriented functions. For example, growers could mark regions that the co-robot is denied entering. Human subject experiments will be conducted to determine the usability and user experiences at different project checkpoints, along with assessment of cognitive task load and other quantifiable human-systems performance measurement such as the task completion time, error rate, and near miss count.

4.5.3. Situation awareness and application safety evaluation

To evaluate situation awareness, safety, and overall system integration performance, StickBug will be tested in a greenhouse environment with participants working in the same space. The robot will work in fully autonomous mode, while the participants will either be equipped with or without the smartphone interface. Participants will be assessed using the Quantitative Analog Situation Awareness Global Assessment Technique (QASAGAT) (Gatsoulis et al., 2010). Objective measurements will also be collected, such as the overall system productivity, human or robotics errors, near misses or robot breakdowns. These measurements will be utilized to guide on how to improve the overall HRI, with the aim to tax less attentional resources on the grower and to maximize the human-robot system productivity when safety requirements are satisfied.

4.6. System Integration and Anomaly Handling

Integrating custom robot hardware designs, software modules, algorithms, environment and human components, leading to predictable and reliable field performance is a highly challenging problem. Building upon past experiences (Gu et al., 2009, 2018a), we will tackle this challenge through a multi-step approach. First, during the robot design process, as a benefit of creating a custom design, the trade between hardware solutions (e.g., designing the robot to reduce/bypass known autonomy challenges) and software solutions will be carefully balanced. Mature design elements and software functions that are known to integrate well are also leveraged to drive down project risks. Second, the autonomy architecture for StickBug will be built upon our proven designs used for planetary rovers (Gu et al., 2018b) and BrambleBee (Ohi et al., 2018; Strader et al., 2019). Third, software integration will happen first in a high-fidelity simulation environment before transitioning to the physical robot, a practice we exercised with BrambleBee. Finally, systematic robot testing in realistic environments will be performed. Different modes of robot anomaly will be discovered and addressed. This point will be discussed further next.

A robotic pollinator working in the field can go wrong in many ways. The robot body and its arms may be trapped by obstacles (e.g., irrigation lines, canes); the robot may damage delicate plant parts or itself; it may also get lost with a diverging localization solution; the computer vision algorithm may fail to pick up a large percentage of flowers when the lighting condition changes, or worse, having many false positives; the robot may experience hardware failures, or running out of power before returning to the charging station. It should be reminded that these are only the fault cases that we can anticipate, which would account for a small portion of the potential failure space. Fundamentally improving a robot's ability to stay productive for long-term, under varying, including unexpected situations, is a long-term research endeavor by the robotics community (Christensen et al., 2020). However, before the “long tail” problem is solved, we can still develop productive robot systems, leveraging nearby humans’ help occasionally. Many abnormal conditions beyond the capacity of robots to reason and address can easily be handled by human workers. To enable this human-robot collaboration, we will develop tools for online self-diagnosis and anomaly detection, risk assessment and prediction, and deciding on which fault mode can be handled by StickBug itself and when to give up and ask for help. We will also develop flexible modes of manual override (e.g., untangle from a cane) with low technological barriers (e.g., powering off the arms so they can be moved by hand).

5. Risk & Mitigation

The use of a holonomic drivetrain simplifies the robot planning and control in tight spaces. For flower pose estimation, we expect it to be less reliable using only RGB cameras, and given the natural symmetries of flowers, there are potentials for ambiguities. If the proposed active perception approach does not work as expected, we would fall back to use RGB-D sensors for the end effectors as on BrambleBee (Strader et al., 2019). The highest risk of the project is anticipated to be the coordinated branch moving and pollination for indirectly reachable flowers. If the proposed method is shown to be unreliable, we would significantly slow down the branch moving motion (to help with flower tracking) with multiple stops along the way to allow better flower association and more chances for the planner to find a feasible pollination trajectory. The reduction of the system integration risk was discussed earlier in Section 4.6.

Several robotic pollination related challenges will not be fully addressed during this project. This includes adapting to more crop/flower types (each would need specialized horticulture study and end-effector design customization), achieving insect-level pollination rate (bees can visit much harder to reach flowers), and long-term autonomy without human supervision.

6. Evaluation

Evaluation of the StickBug's pollination effectiveness will be performed in the WVU Evansdale Greenhouse using two crops: blackberries and tomatoes. Plants will be grown at 25/22 °C (day/night) with ambient light. Four methods of pollination will be used: pollination by bumblebees (*Bombus* spp.), by human hand (manual pollination), by the robot, and no pollination control. Plants will be pollinated at the anthesis (flower opening) in the same room for each species. There will be a minimum of four plants per treatment ($n = 4$). For manual pollination, pollen will be transferred from anthers onto stigmas by hand with a small brush for blackberries, while a vibration tool will be used for tomato pollination. Nettings will be installed in bee pollination areas to prevent cross-pollination from other pollination areas. Although pollination by hand and the robot will be performed with extreme caution, occasional self-pollination is expected to occur. No pollination control allows only natural pollination in the greenhouse and provides a baseline for evaluating pollination effectiveness. The effectiveness of pollination will be evaluated by determining the fruit yield per plant, fruit size, fruit weight, harvest time, the overall distribution of fruit on a plant, pollination speed of each method (flowers per day), and percentage of the pollinated flowers. Also, the cost of bee pollination will be compared to the cost of robotic pollination, including the growers' labor costs for supporting both methods. Additionally, the robot reliability will be evaluated for the mean time between human interventions (Gu et al., 2018b).

The human-robot system performance will be evaluated at both the WVU Greenhouse and a commercial greenhouse (Gritt's Midway Greenhouse, Red House, WV). Gritt's greenhouse has 1.5 acres of hydroponic tomato production. The researchers will conduct observations of eight expert greenhouse growers performing the same tasks, as in Section 4.5, during actual operations while using the robot pollinator. As in the previous phase, we will conduct an HTA, retrospective think-aloud protocol (Van Den Haak et al., 2003) to quantify the impact of the proposed intervention on growers' workload in performing different greenhouse routine operations. The dependent variables will include growers' cognitive and physical load measured by wearable devices (described in Section 4.5), errors of commission and omission and hazard perception, and perceived situation awareness. Each scenario will last 10-20 minutes and the total time for each participant will be less than 2 hours to avoid fatigue. Ample rest will be provided between each trial. ANOVA models (Tabachnick & Fidell, 2007) will be constructed to test the effect of the experimental manipulations on different response measures. In addition, subjective perceived safety, physical work strain index surveys will be administered to investigate grower's satisfaction and perceived safety during the experiment (Hart et al., 1988; Moore et al., 1995; Lasota et al., 2015).

Expected Outcomes and Metrics for Success: the targeted pollination speed for StickBug is 3,600 flowers per day (i.e., average one flower per minute for each of the five pollination end effectors and 12-hour effective work time per day) and the target percentage of the pollinated flowers is 85%.

7. Intellectual Merit

The intellectual merits of this proposed project are twofold. First, the project integrates agriculture domain knowledge, custom robot design, robotics algorithms, and human systems methods to solve a complex real-world challenge. The *complexity* of the problem being tackled, i.e., large-scale manipulation of delicate flowers in diverse situations, is beyond most of the field robots in the past. Knowledge and insights gained through this adventure would advance robotics research in areas such as semantic mapping in dynamic environments, manipulation of deformable objects under occlusions, multi-arm task coordination, and tracking similar-looking objects under motions. More importantly, the emphasis on field testing and comprehensive evaluation of pollinator *effectiveness* will help close the gap between academic robotics research and the needs in real-world applications.

Second, a multifaceted approach is used in this project to *lower the entry barriers* of robotic pollinators. The choices of low-cost hardware reduced the overall system cost, but at the same time introduced additional uncertainties that need to be addressed with algorithms. The research in this area would help popularize low-cost robot's use in different applications. In addition, the integration of human studies in the robot design and evaluation process would help to make the robotic pollination technology acceptable to growers without specialized training. Finally, the open sharing of the pollinator robot design, algorithms, and simulators would promote community collaboration and attract more researchers to innovate in this domain.

8. Broader Impacts

8.1. Impact on Agriculture and the Society

About 80% of all flowering plants require assistance from animals for pollination (USDA Forest Service, 2014) and, without pollinators, many crops cannot propagate (American Bee Keeping Federation, 2014). With the aid of robotic pollinators, growers can overcome the shortage of pollinators and obtain higher profit opportunities by planning flexible pollination schedules independent from the activity of pollinators, producing fruit during early and late season when premium prices are paid for their crops. Pollination robots can also allow for selective pollination and better management of crops by timing and tracking pollinated flowers. With a growing population, increased life expectancy, and limited arable land on Earth, food security has long been recognized as a critical issue. Although the proposed experiments will only be focused on pollination, the developed technology of precision manipulation of delicate plant parts can be further adapted for many other agriculture applications.

8.2. Impact on Education, Outreach, and Workforce Development

Robots, bees, and flowers – this combination of words captures many people's interest and imagination, regardless of their ages. Our multidisciplinary research effort will be tightly integrated with education and outreach activities. For K-12 students, we will explore mixed in-person demonstrations combined with online strategies. Before the COVID-19 pandemic, we have been involved in over a dozen outreach activities each year (e.g., Fig. 6) at different schools, state fairs, and science-themed activities. During the pandemic, we have explored alternative ways of reaching out to students. For example, the PI, Gu, recently talked to several dozen elementary-aged girls about "Bees and BrambleBee" during WVU's Girls' STEM week. Co-PI Gross is on the organizing committee for the WVU Nursery School STEAMPosium that will educate Pre-K to 3rd grade teachers on STEAM educational activities. During this project, we will develop interactive robotic pollination demonstrations with StickBug and an artificial plant that can both be hosted in person and be commanded online (e.g., which flowers to pollinate next?).

Fig. 6. WVU Cataglyphis rover showing off its water bottle picking skills to K-2 students.

For undergraduate students, the StickBug robot design and field-testing components can provide numerous research and learning opportunities. The PI and co-PIs typically have about ten undergraduates working in their labs, supported through different mechanisms (e.g., project funds, NASA prize funds, fellowships, research credits, etc.). PI Gu also sustained a pipeline of undergraduate researchers through advising the WVU Robotic Club, with over 65 members, and the University Rover Challenge (URC) team, with about 30 students. The URC team's manipulator designs are incorporated in the proposed StickBug robot, an example that would show students the potential impact of undergraduate research.

Specific programs will also be developed to integrate the engineering and skilled labor training domains so that future technician training keeps track with the rapidly advancing use of robotics. For instance, hands-on training modules will be developed to train growers on how to work safely and effectively with co-robots in the same space, educate them with the robot's passive and active safety mechanisms. We aim to cultivate strong support for professional greenhouse growers through an active learning (Felder & Brent, 2009) approach (peer co-workers, near-peer mentors, and technical supports), and to lower the barrier of wider adoption. We will assess the success of the workforce development effort through two mechanisms (Frechtling, 2002), 1) formative evaluation: this will be done by working with our industry partners to provide relevant and substantive feedback to the professional outreach and workforce development work; 2) summative evaluation. This will be supervised by our collaborators from the UF College of Education, with data collection and analysis conducted to help understand the effectiveness of the program.

8.3. Broaden Participation of Underrepresented Groups in STEM Education and Research

Research has shown that multidisciplinary programs are often more appealing to a diverse audience (Ouellett, 2005). We will use this project as an opportunity to develop cross-disciplinary curriculum material (for enhancing existing courses) and a series of short educational YouTube videos with emphasis on integrating science and engineering knowledge to tackle real-world challenges (Teppo & Rannikmäe, 2003; Gedrovics, 2006; Machina & Gokhale, 2010). Additionally, the agricultural focus of this project naturally allows us to connect to students from rural regions. Leveraging our NSF-funded robotics REU Site, which led to the creation of a recruiting network of institutions in the Appalachian region, we will continue to encourage students from socio-economically disadvantaged backgrounds and other underrepresented groups to participate in the project.

8.4. Dissemination of Research Findings

Several channels will be exploited to facilitate knowledge sharing and collaborations. As mentioned earlier, we will conduct the project in an open-access fashion (more details in the Data Management Plan). Videos of representative robot experiments will also be shared on YouTube channels to improve the visibility of this project. During our previous pollination project, these videos had been proven to be of high visibility, with media requests after the release of each new video. Some of the media stories have generated several hundred thousand views on social media, indicating a strong public interest in this topic. Our recent media dialogs (e.g., with CNN, AAAS Science) focused on explaining the need for developing backup pollination solutions in the context of bee shortage and the limitations of the current technology. We expect to continue to capture the public imagination with the six-armed StickBug robot and will use this opportunity to better inform the public about the state of pollinators and robotics.

9. Results from Prior NSF Support

Gu/Gross: (a) NSF # 1851815, 03/2019 – 02/2022, $303,310. (b) REU Site on Human-Swarm Interaction. (c) Intellectual Merit: allow one human operator to effectively manage a large robot swarm to achieve desired global objectives, such as search and rescue. (d) Broader Impact: the REU site creates research and learning opportunities for a diverse group of students mainly from socio-economically disadvantaged areas (e.g., five of eight students in the 2019 program were from Appalachia, five were from primarily undergraduate institutions, three were female). (e) Publication: (Dhanaraj et al., 2019).

Hu (Co-PI): (a) NSF # 2026276, 10/2020 – 09/2024, $1,514,197. (b) FW-HTF-RL: Collaborative Research: The Future of Remanufacturing: Human-Robot Collaboration for Disassembly of End-of-Use Products. (c) Intellectual Merit: advance an integrated framework that utilizes the capabilities of both humans and robots in a safe, complementary, and interactive manner, towards designing an economically viable disassembly system for the remanufacturing industry. (d) Broader Impact: the research will allow iteratively adjusted and enhanced collaborative disassembly systems to be implemented in future remanufacturing factories. (e) Publication: N/A.

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