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R2B2 Project: Design and Construction of a Low-cost and Efficient Semi-autonomous UGV for Row Crop Monitoring

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Abstract. *Driving the adoption of agricultural technological advancements like Unmanned Ground Vehicles (UGVs) by small-scale farmers (SSF) is a major concern for researchers and agricultural organizations. They aim for the adoption of precision farming (PF) by SSF to increase crop yield to meet the increasing demand for food due to population growth. In the United States, the cost of purchasing and maintaining rugged UGVs capable of precision agricultural operations stands as a barrier to the adoption of PF technology by SSF. This paper proposes a solution to this barrier by designing and constructing a low-cost and efficient semi-autonomous UGV that can be easily maintained with little knowledge, and adaptable to the specific needs of farmers. This paper introduces the Reduction-To-Below-Two grand (R2B2) project which aims to reduce the cost of commercially available agricultural UGVs for crop health monitoring by developing a semi-autonomous UGV with less than 2000 USD. In this paper, we described the approach taken to achieve cost-effectiveness, and the techniques used in evaluating the performance of the R2B2-UGV on various terrains, data collection efficiency, and battery efficiency. The evaluation revealed that the R2B2-UGV had an average operating time of approximately 11 hours, 10 hours, and 9 hours when operating at speeds of 1.0 m/s, 1.50 m/s, and 2.0 m/s, respectively. Evaluation of the R2B2-UGV's performance on smooth terrain resulted in maximum z-axis displacements of 144 µm, 279 µm, 221 µm, 303 µm, and 352 µm at speeds of 0.50 m/s, 0.75 m/s, 1.0 m/s, 1.25 m/s, and 1.50 m/s, respectively. On undulating terrain, the displacements were significantly higher, measuring 598 µm, 1081 µm, 1719 µm, 2119 µm, and 2597 µm at the same speeds. The R2B2 project demonstrates a significant reduction in the price of developing an efficient ground robot and reveals the possibility of increased adoption of ground robot usage by SSF, thus serving as a driver to the adoption of PF technology and contributing to sustainable agriculture. Future works will focus on* *equipping the R2B2-UGV with a suspension system to reduce vibration, applying machine vision and deep learning technology for plant disease detection, and plant water stress monitoring using the R2B2-UGV.*

Keywords.
UGV, Ground Robot, Precision Agriculture, Artificial Intelligence, Remote Sensing

Introduction

Precision Agriculture (PA) as a means for achieving sustainable agriculture (SA) involves making management decisions based on precise information obtained from the farm. USDA described PA as applying the right resources in the right place and at the right time. To achieve SA through PA, we need to gather as much data as possible from every aspect of the farm with minimal human input. This can be achieved using autonomous robots, which include unmanned aerial and ground-sensing robotic platforms (Messaoudi et al., 2023; Murcia et al., 2021). In recent times, unmanned ground vehicles (UGVs) have been developed and deployed for several purposes including military surveillance, construction site observation, data collection in agriculture, and much more (Mei et al., 2022; Stager et al., 2022).

A review of publications relating to the development and implementation of UGVs reveals some application areas of UGVs on the farm. Researchers developed and utilized UGV platforms for vegetation mapping and sub-canopy plant phenotyping (Cai et al., 2023; Manish et al., 2021; Mueller-Sim et al., 2017). Although the UGV platform developed by Cai et al. (2023) performed plant phenotyping at a significantly reduced cost compared to the PlantEye F500 system (Phenospex; Heerlen, Netherlands), it had a production cost of about 11,780 USD and weighs about 200kg, which may contribute to soil compaction. The Robotanist developed by Mueller-Sim et al. successfully navigated through rows of sorghum autonomously while performing contact-based phenotyping. However, based on a rough estimation of the cost of its components, it had a production cost between 12,000 – 17,000 USD, with a maximum payload capacity of 50kg. Pesticide application is another area that researchers have explored. Jiang et al., (2022) compared the efficiency of using conventional spraying technology, an unmanned aerial vehicle (UAV), and a UGV for pesticide application. They found that the working efficiency of the UGV was 14 times that of the conventional manual sprayer and suggested that it could be improved at the cost of high environmental pollution. However, in contrast to his suggestion, it could be improved by implementing precision spraying technology on the UGV (Baoju et al., 2023). Additionally, researchers have also demonstrated that UGVs can be utilized for when equipped with an edge computing device that can perform machine vision and machine learning operations (Baoju et al., 2023; Sriram et al., 2022). Despite the numerous application areas of UGV on the farm, there have been barriers to its adoption by developing countries and small-scale farmers in the US (Research and Markets, 2022; Schimmelpfennig, 2016), one of which is the cost of obtaining and maintaining commercially available UGVs. A basic Google search showed that the price range for autonomous UGVs suitable for agricultural purposes ranged between 5,000 and 35,000 USD depending on the specifications and adaptability.

Adopting PA for SA is crucial for small-scale farms, which comprise approximately 85% of all farms in the US (USDA, 2023). This adoption is essential to enhance agricultural productivity and meet the growing food demand driven by population increases. This study addresses the adoption barrier by proposing the design of a cost-effective, robust, and versatile UGV tailored to meet the specific needs of farmers.

In this study, we developed the Reduction-To-Below-Two grand (R2B2) UGV, a low-cost skid-steer UGV that can be maintained with little or no technical know-how, which potentially addresses a barrier to UGV adoption by small-scale farmers - the cost of purchasing and maintaining commercially available UGVs. The low cost of developing this ground robot was achieved by thoughtfully selecting chassis and electrical component materials that are cost-effective and durable.

The paper is structured as follows, Section 2 covers the developed vehicle and its core navigation algorithm, while Section 3 outlines the methods employed to evaluate the vehicle's performance, along with the corresponding results, and Section 4 summarizes the content of the paper.

Materials and Methods

Hardware Components

The chassis of the vehicle was designed using a free online software- SketchUp™ having in mind three design considerations: (i) the cost; a low-cost autonomous farm robot, (ii) the size; a UGV that could navigate through the rows of crops like corn and wheat that are predominant in South Dakota, and (iii) the weight of the UGV; to maximize its payload capacity. Figure 1 shows orthographic views of the vehicle.

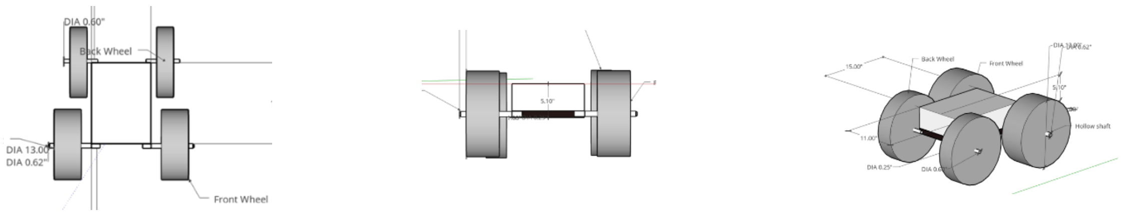


Figure 1: Orthographic views of the UGV

The proposed vehicle is a four-wheel, skid-steer UGV. It is a forward-wheel drive (FWD) vehicle equipped with two brushless direct current (BLDC) motors (obtained from a hoverboard- model HY-RM-ULTRA) and two trailing tires. The chassis of the vehicle was fabricated by welding a 1-inch angle iron (15 × 11 inches), two metal pipes of length 3 inches (5/8-inch inner diameter), and two steel rods of length 4 inches were welded to the frame. The axles of the motors are attached to these metal pipes. Figure 2 displays all hardware components and wiring of the R2B2-UGV which includes the chassis, electrical components, and perception components. It has a total weight of 20 kg and a payload capacity of up to 70 kg.

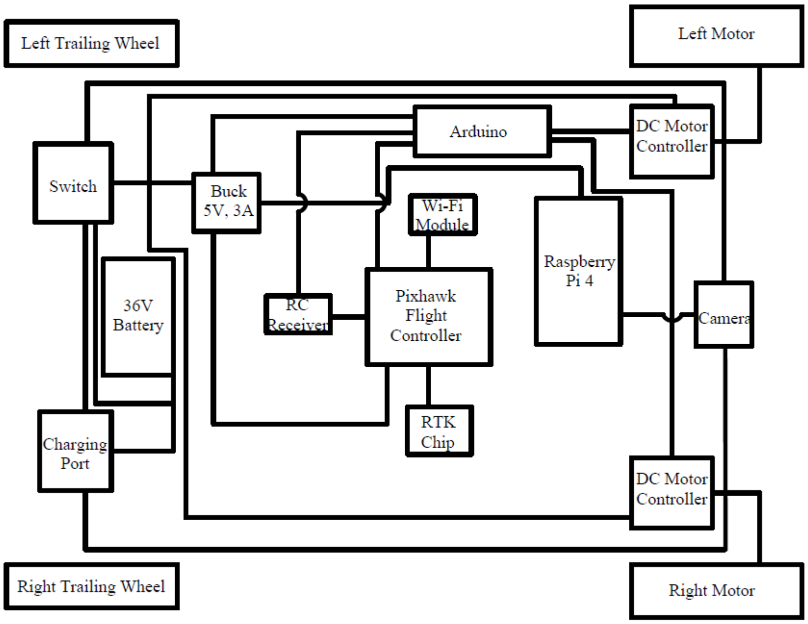


Figure 2: R2B2-UGV hardware components

The R2B2-UGV is powered by a 36 V rechargeable Li-ion battery (Shenzhen Longting Technology Co. Ltd, Guangdong, China). The 350 W BLDC motor controllers (model-KJL-01, RioRand) receive 36 V directly from the battery to run the motors. A buck converter is connected in series to the battery and supplies 5 V to the Pixhawk flight controller (PFC), Arduino UNO microcontroller (Arduino, Somerville, MA, USA), and Raspberry Pi 4, concurrently. The PFC supplies power to a Wi-Fi module (ESP8266MOD), a Real-time Kinematic GPS (RTK-GPS), and an RC receiver, while the Raspberry Pi 4 powers the RGB camera (AR0234, Arducam, Shanghai, China). Figure 3 shows the power distribution in the system.

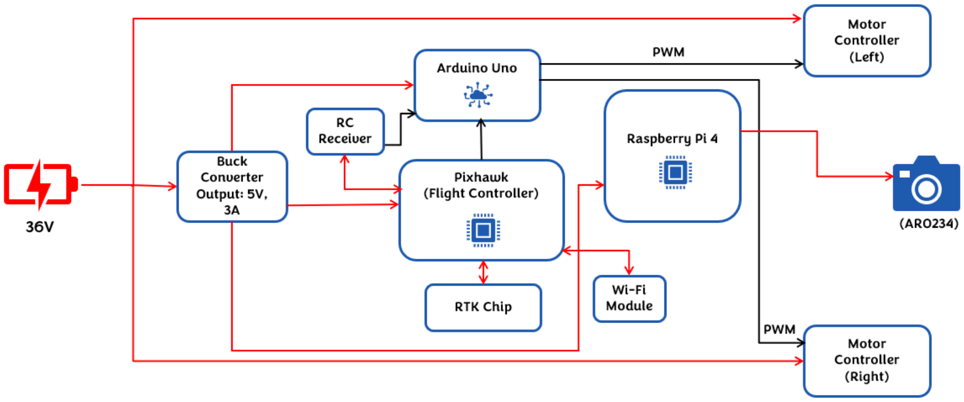


Figure 3: Power distribution in the R2B2-UGV

Navigating The Vehicle

The control of the R2B2-UGV is made possible using an algorithm written on the Arduino IDE. The microcontroller receives PWM signals from the PFC and the RC receiver and sends out amplified PWM signals to control arming/ disarming and navigating the vehicle based on the algorithm. The algorithm is simplified as shown in Table 1.

Table 1: Algorithm to Achieve Manual Navigation of The Vehicle

Navigation Algorithm

```
Input: PWM signals for throttle, steering, reverse, and arming the vehicle.
Output: Amplified PWM signals for throttle, brake, and direction of left and right motors.
Repeat
    If vehicle is armed
        If throttle value $> 1010$
            If steering value $> 1450$ & steering value $< 1550$
                If forward
                    Move forward with speed = throttle value
                Else if reverse
                    Move backward with speed = throttle value
            Else if steering value $< 1450$
                Turn left
            Else if steering $> 1550$
                Turn right
        Else if throttle value $< = 1010$
            Activate brake
    End if vehicle is unarmed
```

The control of the vehicle is in two modes: (i) manual navigation by using the RC transmitter (RCT), and (ii) autonomous navigation by remotely controlling the R2B2-UGV by uploading waypoints via Wi-Fi from a ground station. Both navigation modes are activated by arming the vehicle and sending a designated range of PWM signals via a channel on the RCT. Figure 4 shows the wiring setup for navigation.

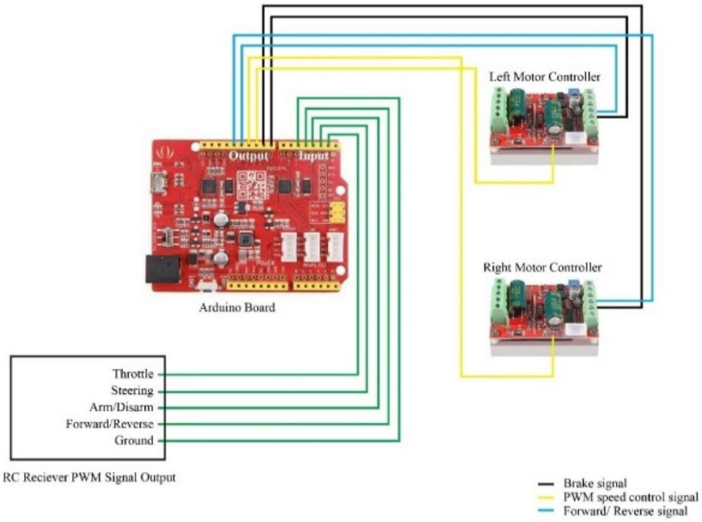
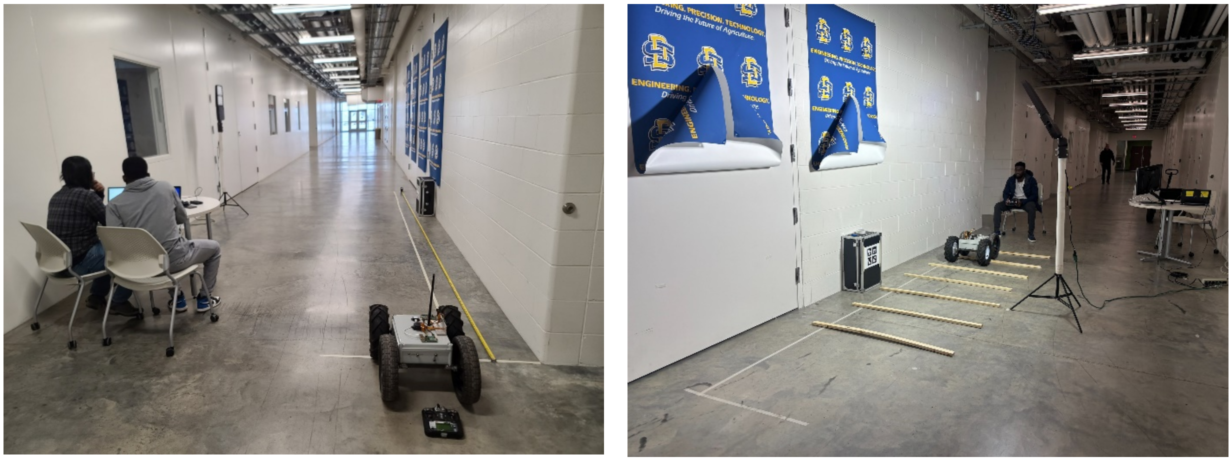


Figure 4: Navigation wiring of the R2B2-UGV

Performance Evaluation of the R2B2-UGV

Three experiments were conducted to evaluate the performance of the R2B2-UGV. First, we assessed its battery efficiency. This test involved running the R2B2-UGV at constant speeds of 1.0 m/s, 1.5 m/s, and 2.0 m/s, and recording the time until battery depletion for each speed. Each run was performed after a full charge of the R2B2-UGV (approximately 4 hours and 15 minutes) and was repeated three times to ensure accuracy.

The second experiment, a 5 × 2 factorial experiment, measured vibration displacement along the z-axis. A 3-axis vibration sensor (WTVB01-BT50, WitMotion, Shenzhen, China) was mounted on the R2B2-UGV with an adhesive and connected via Bluetooth to a smartphone for real-time data collection. We assessed the effects of varying speeds of the R2B2-UGV (0.5 m/s, 0.75 m/s, 1.00 m/s, 1.25 m/s, and 1.50 m/s) and terrain conditions (smooth and undulating) on the vibration displacement in the z-axis direction of the vehicle over a duration of 8 seconds. The smooth terrain was a smooth concrete floor, and the undulating terrain was simulated by placing and fastening wood blocks with an adhesive (19.05 x 38.1 x 1219.2 mm) at 482.6 mm intervals to create an undulating ground. Figure 5 shows the smooth and undulating terrain conditions.



(a) Smooth terrain

(b) Undulating terrain

Figure 5: Smooth and undulating terrain conditions

Lastly, to assess the R2B2-UGV's capability for image data collection, we conducted a 4 x 3 x 2 factorial experiment to compare a global shutter camera and a rolling shutter camera in a pattern recognition task. In this experiment, a YOLOv8 model was trained and deployed to two Raspberry

Pi 4 units which were mounted on the R2B2-UGV to control both cameras. The reader is advised to see Kemeshi et al. (2024) for more details about this experiment. Figure 6 shows the cameras and the vibration sensor mounted on the R2B2-UGV.

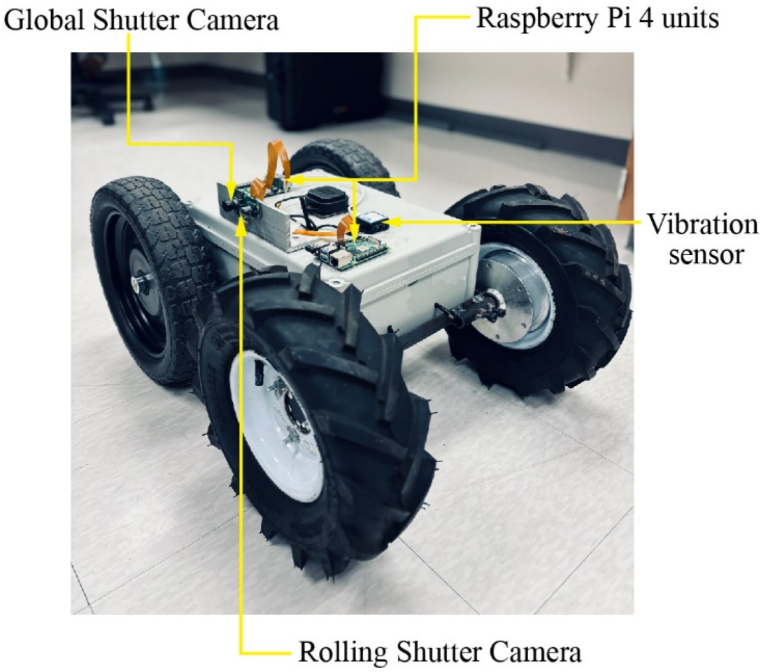


Figure 6: Cameras mounted on the R2B2-UGV

Results and Discussion

Battery Efficiency Test

An experiment was conducted to assess the battery efficiency of the R2B2-UGV without load and results are displayed in Table 2. The data shows that as the speed increases, the battery depletion time decreases. It indicates that the R2B2-UGV efficiently utilized its battery power.

Table 2: Battery Efficiency of the R2B2-UGV

Speed (m/s)	**Replicate 1** Time (Hours)	**Replicate 2** Time (Hours)	**Replicate 3** Time (Hours)	**Average** Time (Hours)
1.00	11.2	11.0	11.1	11.10
1.50	10.2	10.3	10.2	10.23
2.00	9.5	9.3	9.3	9.37

Vibration on Different Terrains

Figure 7 displays the plots of the raw displacement data obtained from the smooth terrain in the experiment. A thorough observation of the plots will reveal an increase in displacement in the z-axis with increasing speed. The peak values in the z-axis displacement signal increased from less than 150 µm to 350 µm. This increasing displacement was due to the vibration caused by the unevenness in the smooth terrain, and some components in the R2B2-UGV that were not well fastened.

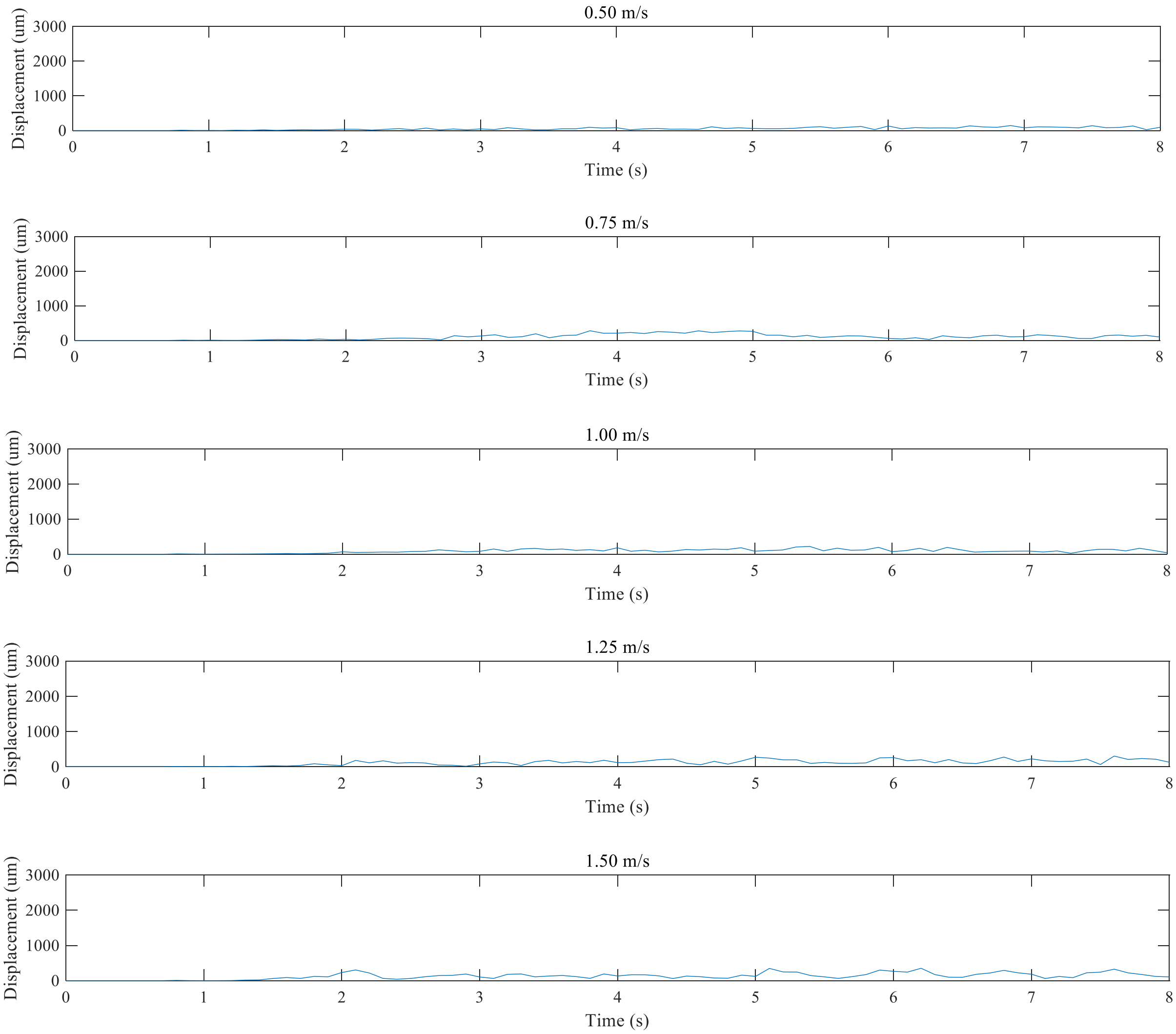
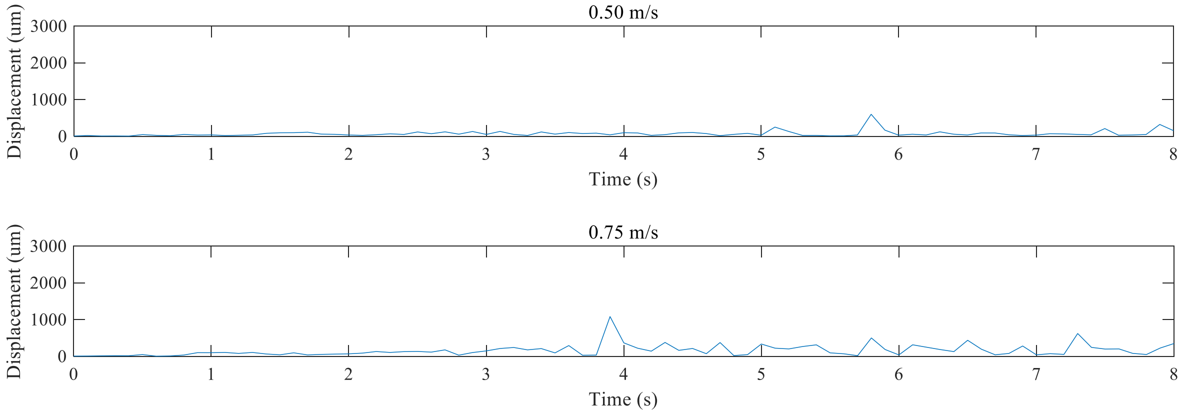


Figure 7: R2B2-UGV z-axis displacement on the smooth terrain

The z-axis displacement plot of the R2B2-UGV from the undulating terrain is shown in Figure 8. It shows a dramatic increase in the z-axis displacement compared to that of the smooth terrain. Peak values ranging from approximately 500 µm to 2500 µm can be observed from the plots with increasing speed, and these values correspond to periods when the R2B2-UGV navigates over the wood blocks used in simulating the undulating ground.



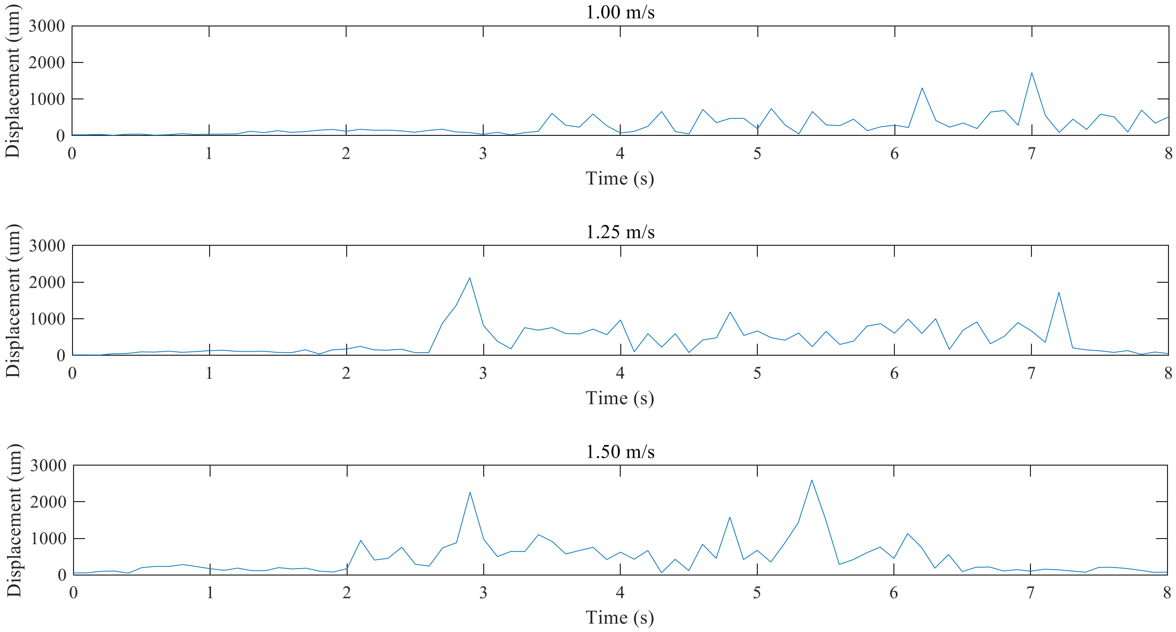
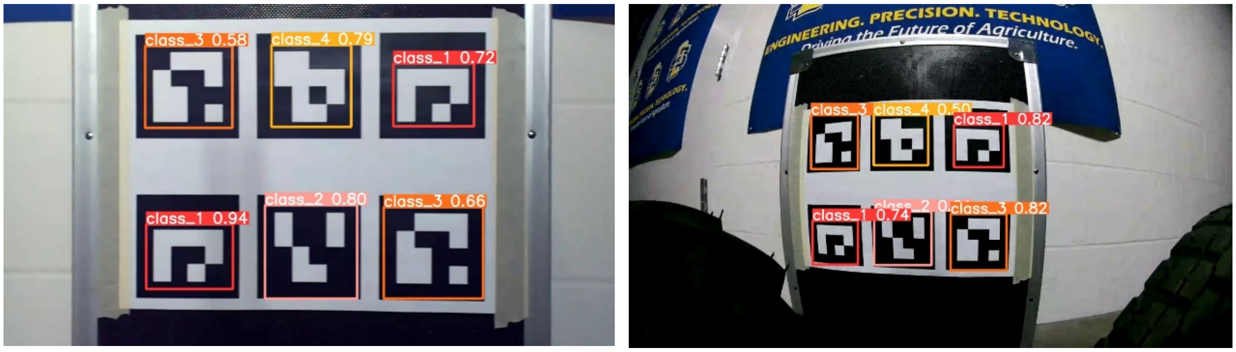


Figure 8: R2B2-UGV z-axis displacement on the undulating terrain

Image Data Collection Using the R2B2-UGV

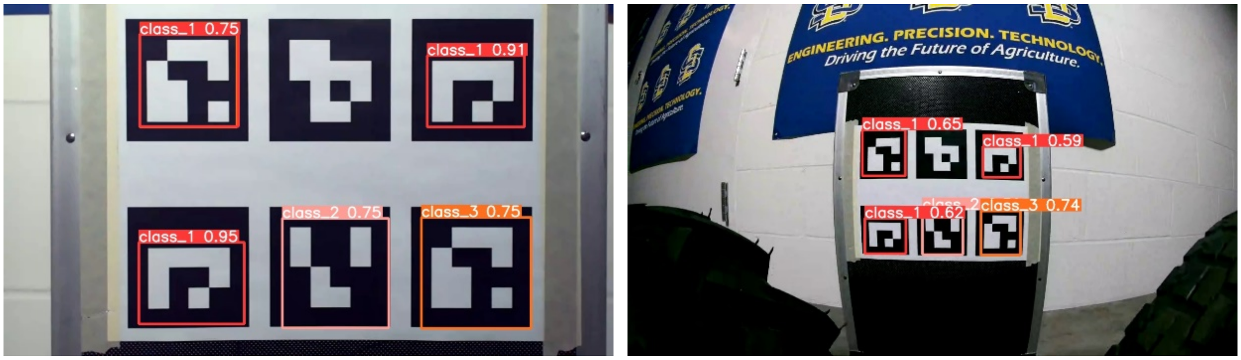
The results of this study showed that the R2B2-UGV was capable of image data collection in varying terrains. Figures 9 and 10 show frames captured from both cameras as the R2B2-UGV moved at a speed of 0.75 m/s on smooth and undulating terrains, respectively.



(a) Global shutter camera

(b) Rolling shutter camera

Figure 9: Frames captured from both cameras on smooth terrain



(a) Global shutter camera

(b) Rolling shutter camera

Figure 10: Frames captured from both cameras on undulating terrain

Conclusion

In this paper, we introduced the Reduction-To-Below-Two grand (R2B2) project which proposes a solution to a barrier facing the adoption of unmanned ground vehicles by small-scale farmers. We showed the components of the vehicle and its algorithm for manual navigation. We assessed the performance of the vehicle in terms of battery efficiency, vibration, and data collection. The battery efficiency test revealed that the R2B2-UGV can run for approximately 11 hours, 10 hours, and 9 hours at speeds of 1.0 m/s, 1.5 m/s, and 2.0 m/s, respectively. We observed that the z-axis displacement of the R2B2-UGV on the smooth terrain had peak values of 144 μm, 279 μm, 221 μm, 303 μm, and 352 μm at speeds of 0.50 m/s, 0.75 m/s, 1.0 m/s, 1.25 m/s, and 1.50 m/s, respectively, and 598 μm, 1081 μm, 1719 μm, 2119 μm, and 2597 μm at the same speeds for the undulating terrain. Furthermore, we demonstrated the ability of the R2B2-UGV to collect image data. The success of the R2B2-project indicates that cost reduction in the price of developing UGVs can be achieved by optimal selection of cost-effective materials and components.

In the future, the z-axis displacement data will be considered in the design of a cost-effective suspension system and adaptive terrain model to achieve better stability in the vehicle. Furthermore, the vehicle will be utilized for real-time crop monitoring and disease detection using machine vision and deep learning algorithms.

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