Wholesome Robotics

Conceptual Design Review

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Date: 8th December 2018

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1 Project Description

Organic vegetable farming introduces several challenges for farmers in achieving high-quality crops and high crop yield. Most notably, without artificial pesticides and herbicides, it is extremely challenging to control the invasion of pests and weeds into the crop beds. Pests may directly harm the crops by eating them or spreading diseases. Weeds pose an additional threat by depriving plants of nutrients and space. The longer an infestation goes unnoticed, the more difficult it becomes to control. Therefore, it is of the utmost importance for organic farmers to monitor their fields for weed and pest pressures in order to prevent more widespread damage.

Robotic monitoring and weeding of organic vegetable farms pose a potential solution. Mitigating diseases and pests is very specific to each threat, and a robot which could handle every threat it encounters would be prohibitively complex. However, a robot which can automatically survey the field for disease and pest pressure, and deliver reports on disease and pest pressure to farmers so that they may respond in a timely and informed manner would deliver significant value to farmers. In addition, removing weeds from fields organically is very labor intensive, however, we believe that the task is not outside of the reach of a robot. A robot which could remove weeds when it encounters them would add significant value to organic vegetable farms.

2 Use Case

2.1 Narrative

The robot will operate in three modes, there is a use case for each:

Mapping

On a sunny day, the technician brings the robot to the field, selects the mapping mode and places it at the start of the first row. The technician moves the robot manually (joystick controlled) through the field for the first time. The robot collects visual and location data. The user then moves the robot back to the barn and connects it to the docking station. Later the visual data is labeled manually to create a map of the location and the plants in each row.

Monitoring

On a sunny day, the user moves the robot to the field, selects the monitoring mode and places it at the start of the first row. The robot autonomously collects visual data from the field by autonomously shifting through the rows and not crushing plants while traversing through a row. After collecting data the robot reaches the starting point again from where the user moves the robot back to the barn and connects it to the docking station. The robot processes the data and provides insights to the user about pests/signs of pests/disease in the form of heat maps, location, and trends in pests.

Weeding

On a sunny day, the user moves the robot to the field, selects the weeding mode and places it at the start of the first row. The robot autonomously moves through the row, stopping when it detects weeds. The robot uses a weeding method to kill the weed around the brassica plants. Finally, after weeding the entire field, the robot traverses back to the starting point. The user moves the robot to the barn where it is connected to the docking station. The robot evaluates the work done and provides the user an update about the weed pressure and the weeding operations performed.

2.2 Graphical Representation
Mapping Mode

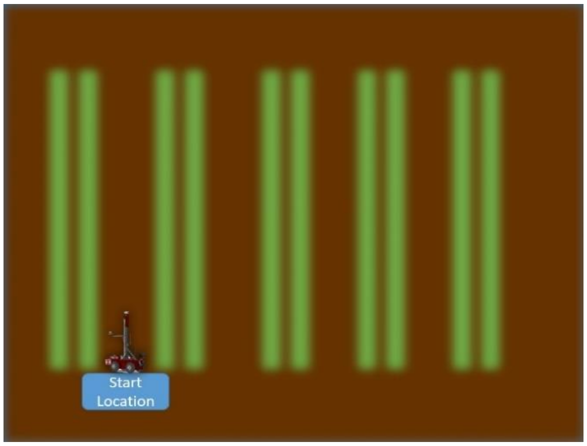

Figure 1 On a sunny day the user carries the robot to the field, selects the mapping mode and places it at the start of the first row

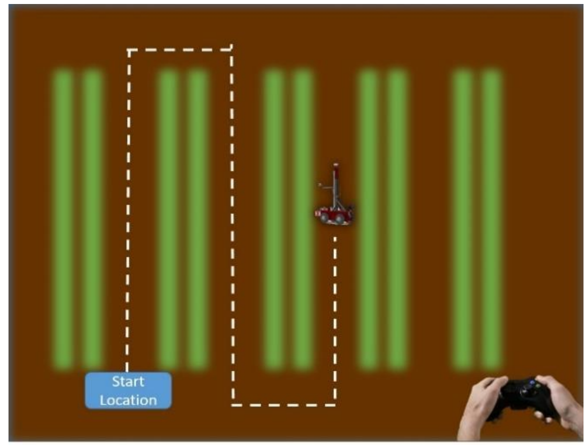

Figure 2 The user moves the robot manually (joystick control) through the field for the first time

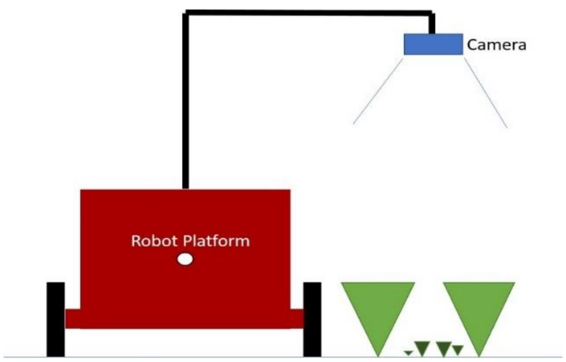

Figure 3 The robot collects visual and location data while moving through the field.

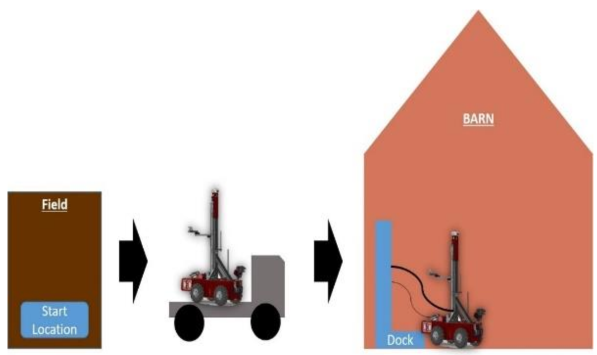

Figure 4 The user then carries the robot back to the barn and connects it to the docking station

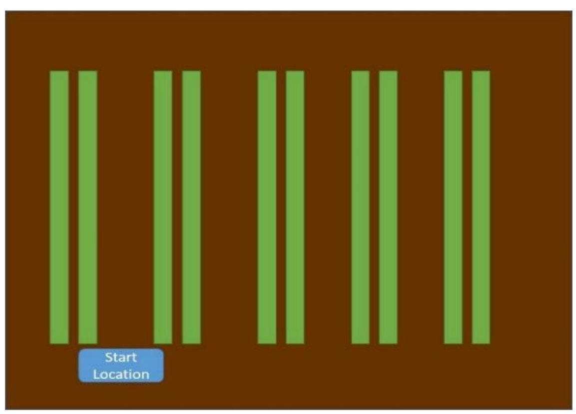

Figure 5 The visual data is labeled manually to create a map of the location and the plants in each row

Monitoring Mode

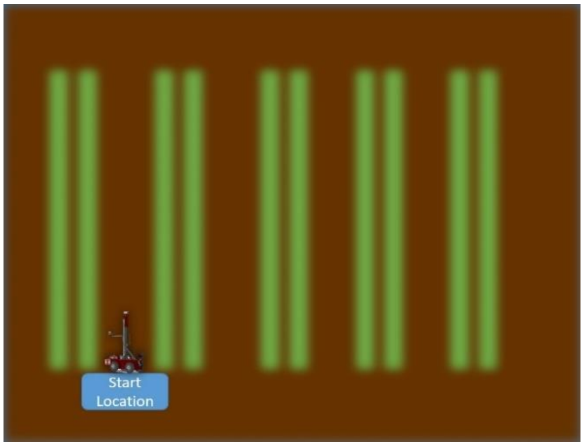

Figure 6 On a sunny day the user carries the robot to the field, selects the monitoring mode and places it at the start of the first row

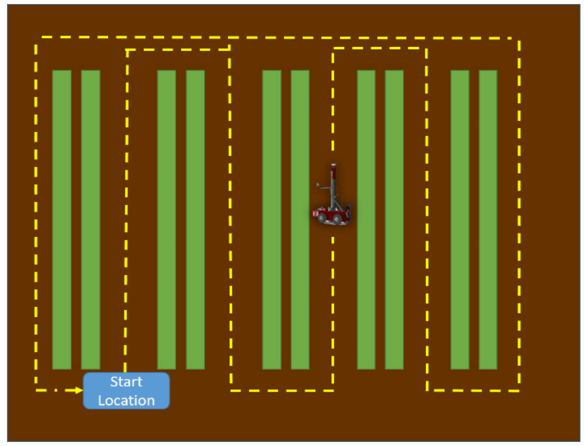

Figure 7 The robot autonomously collects visual data from the field by autonomously navigating through the field and reaches back to the starting point

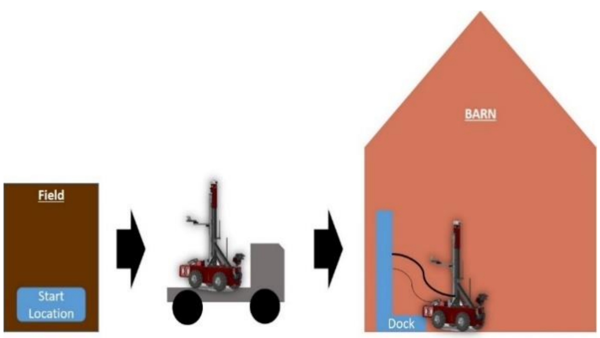

Figure 8 The user carries the robot from the starting point back to the barn and connects it to the docking station

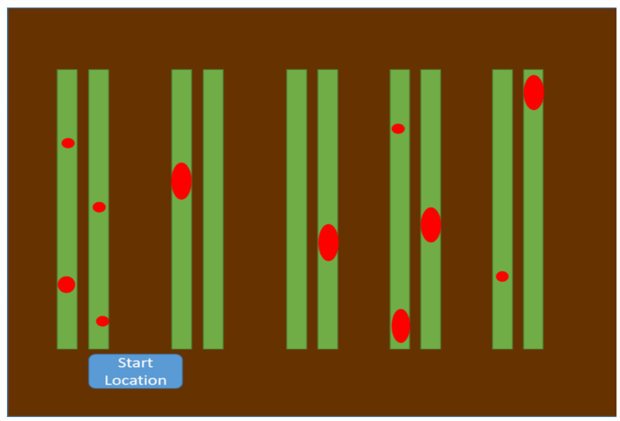

Figure 9 The user then carries the robot back to the barn and connects it to the docking station

Weeding Mode

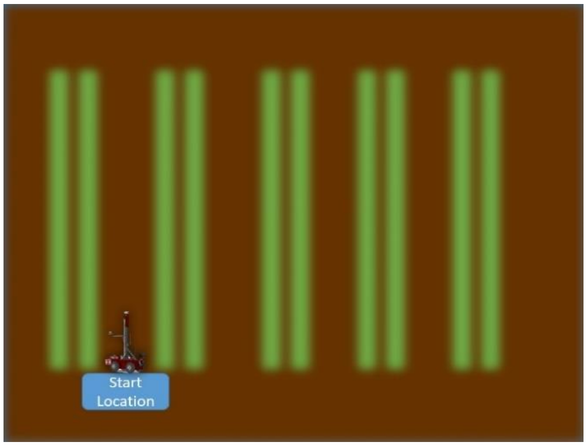

Figure 10 Figure 10 On a sunny day, the user carries the robot to the field, selects the weeding mode and places it at the start of the first row.

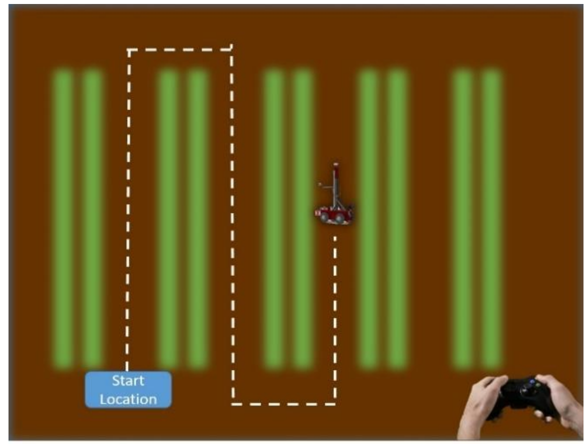

Figure 11 The robot autonomously moves through the row, stopping when it detects weeds

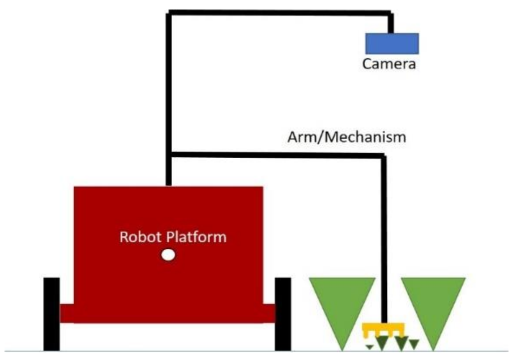

Figure 12 The robot uses weeding method to kill the weed around the brassica plants. Finally, after weeding the entire field, the robot traverses back to the starting point

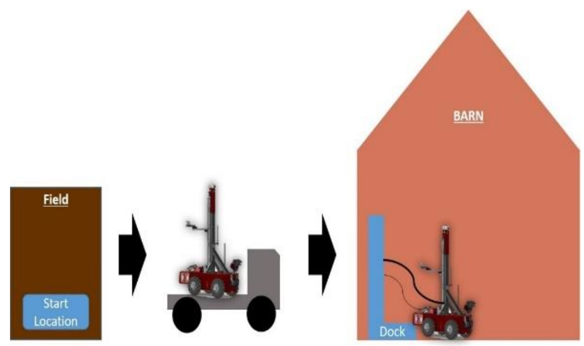

Figure 13 The user picks up the robot from the starting point and carries it to the barn where its connected to the docking station

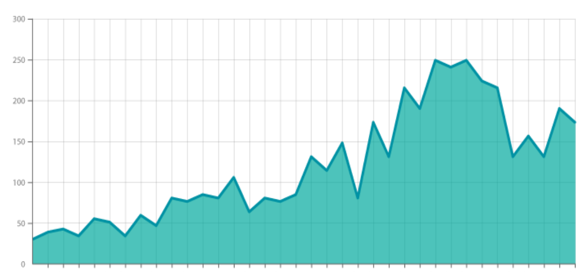

Figure 14 The robot evaluates the work done and provides the user an update about the weed pressure and the work done

3 System Level Requirements

3.1 Functional Requirements

Table 1 Functional Requirements

The Robot shall:

FR1. Take input from the user
FR2. Build a map of the field
FR3. Perceive drivable area during navigation
FR4. Autonomously localize itself
FR4.1. Along Row
FR4.2. Correct Row
FR5. Autonomously switch between rows of the field
FR6. Collect visual data
FR7. Identify weeds online
FR8. Localize weed online
FR9. Identify signs of disease
FR10. Identify pests or signs of pests
FR11. Kill weeds when plants are small
FR12. Generate meaningful reports
FR13. Communicate (reports) to users

Note: FR connotes a Functional Requirement.

3.2 Performance Requirements

Table 2 Performance Requirements

The Robot will:

MR1. Take input from the user with 10 Hz signal rate
MR2. Build a map of the field with <15% dimensional error in row width and length
MR3. During navigation perceive drivable width of a row within -10% error bound
MR4. Autonomously localize itself
MR4.1. In the correct row with 95% accuracy
MR4.2. Along row with mean error < 24in
MR5. Autonomously switch between rows of the field with 80% success rate
MR6. Collect visual data with 75% usable images
MR7. Identify weeds online with false positive on plant < 5%, false negative < 30%
MR8. Localize weed online with positional error w.r.t the robot frame < 2in
MR9. Identify signs of disease on plant with false positive <20%, false negative < 20%
MR10. Identify pests and /or signs of pests with false positive <20%, false negative <20%
MR11. Kill weeds when plants are small with 75% success rate
MR12. Generate meaningful reports within 24hrs of collection
MR13. Communicate (reports) to users within 1s of request

Note: MR connotes a Mandatory Requirement, DR connotes a Desirable Requirement.

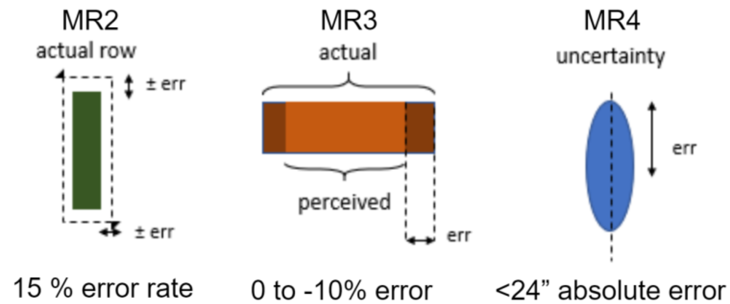

Figure 15 Graphical Representation of Selected Performance Requirements

3.3 Non-Functional Requirements

Table 3 Non-Functional Requirements

The robot will:

MN1. Fit in the row of width 24in
MN2. Accommodate various control modes via kill switch and joystick
MN3. Be weather resistant at least IP 20
MN4. Have sufficient battery capacity for a complete run of Rivendale brassica field
MN5. Not damage plant during navigation
MN6 Not damage plant during weeding
DN1. Have indicators for system health (sanity checks)
DN2. Be easy to repair
DN3. Fit in Hillel's Subaru with 73.3 ft3 of cargo space

Note: MN connotes a Mandatory Requirement, DN connotes a Desirable Requirement.

4 Functional Architecture

The functional architecture has been divided into three parts according to the selected mode. The first mode is the Manual Mapping Mode. Here a technician moves the robot through the field through manual control. The robot collects data during this time which is manually labeled to create a map. The second mode is the Weeding mode where the robot autonomously moves through the field using the localization and navigation blocks. It identifies and localizes weed and then attempts to kill them. In the end, a report is generated about the weeding done and is communicated to the user. The third mode is the monitoring mode, here the same navigation and localization blocks are utilized to navigate through the field. The robot collects visual data which it processes later to identify signs of pests and disease. In the end, meaningful reports are generated to communicate to the user information about the crop health.

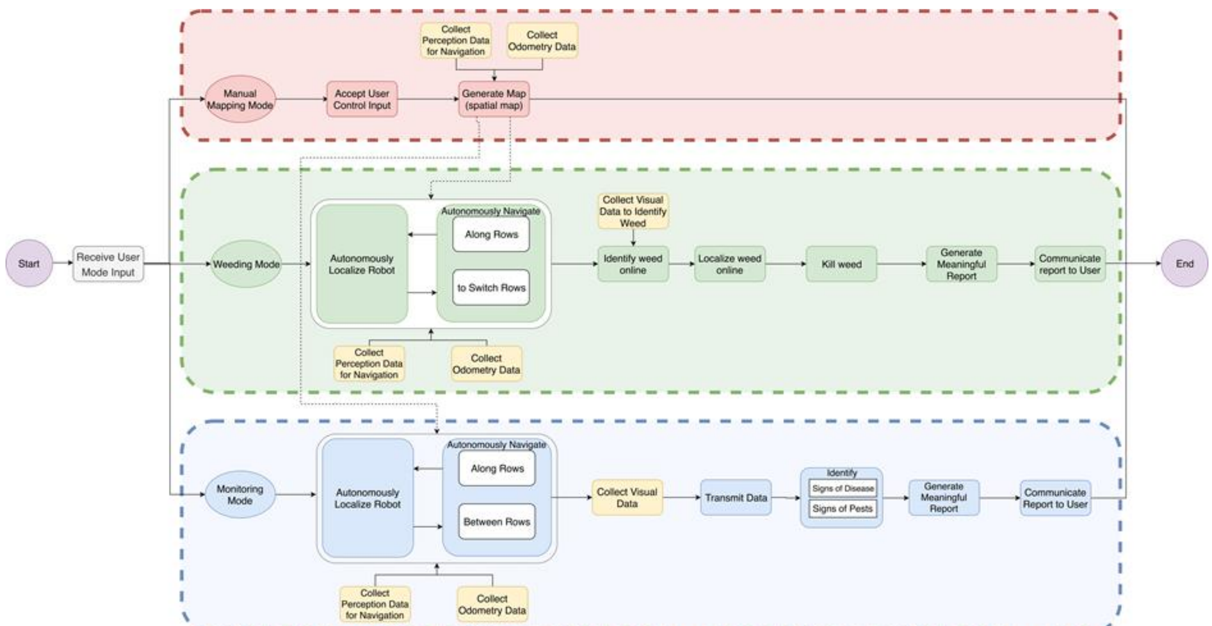

Figure 16 Functional Architecture

5 System Level Trade Studies

5.1 Robot Platform Trade Study

The robot platform consists of the hardware required for mobility of the system including hardware and software. The platform will be used to mount the sensors and the manipulator and will traverse the field. The Robot Platform trade study aims to find an optimal platform for the system which will adhere to all relevant requirements of the system.

Table 4 Robot Platform Trade Study [1] [2] [3] [4] (Parameters rated out of 5)

Parameter	Weight %	Jackal	Husky	4WD Rover	Flipper Rover	Robotanist
Width of Robot	25	4	2	5	5	3
Speed of Robot	10	4	2	5	3	4
Lateral Stability	20	2	4	1	1	5
Payload Capacity	25	2	5	3	3	4
Run Time	5	5	2	3	3	5
Wheel base	15	5	2	4	4	1
Weighted Sum	100	3.3	2.95	2.93	2.81	**3.44**

The criteria considered were the width of robot (to ensure the robot can fit in row 24" wide), lateral stability (to ensure that the robot does not topple while moving along a row), payload capacity (to ensure that the robot is able to carry the required sensor and manipulator payloads), speed of the robot (to ensure that the robot covers the required area in the given time), battery runtime (to ensure that the robot has enough power to do the required tasks for the entire brassica field on a single charge), and the robot's turning radius (to ensure that the robot can switch rows with ease). Through the trade study, the Robotanist platform [5] was considered suitable for the project.

5.2 Weeding Manipulator Trade Study

The manipulator arm is essential for completion of the weeding task. In order to assess various manipulation techniques, we compared a few aspects of the different options and weighted the values of these benefits as they pertained to our project. For example, the stability of the manipulator, which corresponds to the manipulator's ability to remain in a single desired pose, is rather important for the operation of the weeding mechanism. Manipulators with shorter limbs or screw threading actuators were given a higher rating. Other metrics included the speed at which the mechanism would be able to move (a screw threading would move slower than a servoed joint) the size of the apparatus is relatively unimportant as it will be the only moving part other than the driving platform itself. The precision of the manipulator's pose directly correlates to the success of the weeding operation, while the ease of use considers the degree of difficulty we will encounter trying to implement the system. Finally, the cost is always an important factor to consider.

Table 5 Weeding Manipulator Trade Study (Parameters rated out of 5)

	Weight (%)	6 DOF arm	Straddling Gantry	Telescoping 3 axis	Telescoping shoulder joint
Stability	20	3	5	2	1
Speed	20	5	3	1	3
Size	5	2	3	2	3
Precision	20	5	4	3	2
Price	20	1	5	5	3
Ease of use	15	1	4	5	3
Value		3.05	4.15	3.05	2.4

The straddling gantry is highly superior, but it presumes a specific type of driving platform. Specifically, there would need to be drive wheels in two adjacent travel rows and the robot would straddle the plants in between. Since this is not a possibility, we are left to choose between the 6 DOF arm and the telescoping 3 axis configurations; however the cost of a 6 DOF arm was prohibitive relative to our funding, so we settled on the telescoping 3 axis configuration.

5.3 SLAM Trade Study

The SLAM trade study compared the state-of-the-art SLAM systems in order to choose an algorithm ideally suited for the mapping and localization of the robot in the rows of crops at Rivendale Farms.

Table 6 SLAM Trade Study (Parameters rated out of 5)

Parameter	Weight (%)	Visual Lidar Odometry (V-LOAM)	LSD SLAM	ORB SLAM	RTAB-Map	Hector SLAM
Kind of map generated	30	3 Sparse	4 Semi-Dense	3 Sparse	5 Dense	3 Sparse
Sensors required and compatibility with pipeline	20	5	5	5	2	3
GPU requirements	10	5	5	5	5	5
ROS Package availability	10	5	5	5	5	5
Deviation from the desired trajectory in indoor environments	30	3.74	3.92	2.89	1.39	5
Value	100	4.022	4.376	3.76	3.317	4

*(*Note: The cost of the 3D LIDAR has not been included because of its availability in FRC and MRSD inventory)*

A number of parameters were taken into account during this study which includes the kind of map generated (higher density maps are more robust to change and are therefore given higher weight), the number and cost of the required sensors, the GPU requirements, and ROS compatibility. Special consideration was given to the performance of the algorithms in outdoor environments. Accuracy in indoor environments has been considered a rough metric to estimate the efficiency of the SLAM algorithm because of the lack of research comparing the performance of these algorithms in an outdoor setting. A general understanding of the algorithms and previous results from outdoor experiments were utilized to assess the potential performance in outdoor environments. Potential performance of the sensors in use for the algorithm has also been considered. For example, if the plant row does not provide a feature-rich environment, a ‘Direct’ SLAM approach will be preferred over a ‘Feature-based’ SLAM approach.

The algorithms considered were: LSD SLAM – a Direct Visual SLAM [6] approach for working in feature-less environments by directly tracking changes in photometric consistency over frames; ORB SLAM – a state of the art, feature-based Visual SLAM approach [7]; V-LOAM – a state of the art Visual SLAM approach which utilizes 3-D Lidar and Visual odometry to fuse information for SLAM [8]; Hector SLAM – an approach using 2D Lidar to generate a 2D map of the environment; RTAB Map – a method that uses both depth and RGB data (RGB-D) for SLAM [9]. Currently, LSD SLAM is considered most suitable for this project

5.4 Perception Algorithm Trade Studies

5.4.1 Weeding Perception

Figure 17 A visual example of the problem we are trying to solve. Green prickly plants are weeds and red plants are the crops.

The weeding perception problem is essentially broken down into (1) localization of the weed in the image frame (RGB, depth, or both) and (2) localization of the weed in the robot frame.

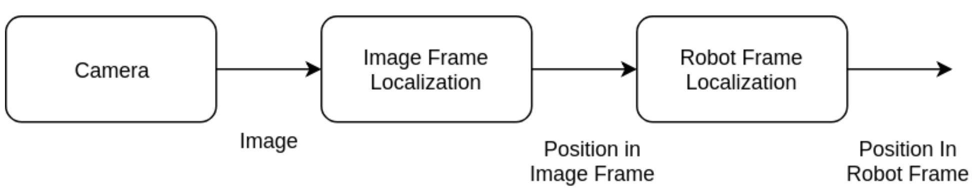

Figure 18 High level breakdown of weeding perception

Localization in Image

One state-of-the-art approach to object detection involves using convolutional net based object detector to recognize weeds, such as a Single Shot Detector (SSD) architecture [10]. This architecture predicts object bounding boxes from feature maps at various scales. However, one source of error in this case is the image plane location error resulting from the discretization of the boxes by the convolutional net, which is done in order to make training the net feasible. We can build an architecture suited to our application which predicts bounding boxes only at the scale expected from the camera intrinsics, extrinsics, and target weed size, with a discretization which will achieve our performance requirement of 2 inches maximum weed localization error. We can use pre-trained feature layers to generate feature maps in order to reduce the amount of training data needed.

Another approach which does not discretize the space of object locations would be to use a semantic segmentation approach based on a fully convolutional network (FCN) [11] which produces an image segmentation where each segment has been labeled with an object class. This has the drawback of increased computational load. It is also possible to combine the two approaches, doing semantic segmentation only inside the predicted bounding boxes in order to get more accurate location estimates. In this can also use pre-trained feature layers to cut down on the amount of training data needed.

Table 7 Comparison of various methods for localizing weeds in the image (Parameters rated out of 5)

	Weight (%)	Image Segmentation + Segment Classification	CNN Semantic Segmentation	CNN Object Detection
Generalizability	30	3	5	5
Real-time Operation Speed	35	5	3	4
Accuracy	35	3	4	4
Total	100	3.7	3.95	4.3

Localization in Robot Frame

Once the position of the weed, and possibly a segmentation or bounding box is obtained, the position of the weed in 3D space must be obtained. One approach involves only a monocular camera. Using camera intrinsics and extrinsics, a ray can be traced from the image plane and intersected with the ground plane in order to compute a 3D location. While this approach is promising, the error in the estimation of the pose of the ground plane, and the divergence from the soil from an idealized planar model poses an issue. In order to mitigate this, a depth camera or lidar could be used to better estimate the ground plane or directly measuring the 3D position of the weed, once classified. The current direction is, therefore, to combine the depth and RGB information from an active lighting stereo camera in order to obtain a position estimate of the weed in 3D space.

5.4.2 Monitoring Perception

Table 8 Monitoring Perception Trade Study (Parameters rated out of 5)

Type	Weight (%)	Binary Segmentation	Faster RCNN + GAN + object tracker	YOLO + GAN + object tracker
Detection Accuracy	40	2.5	5	4
Information Gained	40	3	5	5
Low Complexity	20	5	3	3
Value		3.2	4.6	3.4

The computer vision algorithm is essential for monitoring plant health regarding disease and signs of pests (such as holes). We compared a few aspects of the different options and weighted the values of these benefits as they pertained to our project. For example, the information gained corresponds to the size (measured in area) and prevalence (how many holes there are) of the damage. Generative networks are capable of segmenting while object trackers can maintain a reference to absolute numbers of disease/signs of pests. Other metrics included the detection accuracy and implementation complexity. Note that since the computation is done offline, speed is not considered as a criterion. The Faster RCNN + GAN + Object Tracker turned to be the best choices as it has the highest detection accuracy while having the same score as YOLO in other criteria.

5.5 Sensor Trade Study

Table 9 Perception Sensor Trade Study

Type	Weight (%)	Intel RealSense	Custom made Active Lighting Stereo - Small	Custom made Active Lighting Stereo - Tiny	ZED
Range Accuracy	*10*	5	4.5	4.5	4.5
Generate Useful Data	*40*	3	5	5	3
Low min distance	*10*	4	5	5	3
Low weight	*20*	5	4	3.5	5
Robustness	20	5	4	3	5
Value		4.35	4.6	4.49	4.05

Assuming we are using a neural network for weeding and plant health perception, the quality of RGB-D data would directly affect the outcome of these tasks. It is assumed that weeding and plant health monitoring share the same sensor, and hence the trade study criteria must account for both modalities. We compared a few key aspects of the different sensor options and weighted the values of these benefits as they pertained to our project. For example, generating useful data is key to the success of this task, because there is a relatively limited amount of data available from the field; hence, sensors with active lighting have a great advantage. Other metrics included the range accuracy, which would affect the accuracy of localization in weeding, and the minimum installation distance between target and sensor (this is usually demanded by stereo cameras). Since the sensor would be cantilevered the weight of the sensor is crucial, as heavier sensors could affect the stability of the overall robot platform. Although Intel Realsense is rather lightweight and has high range accuracy, it is subject to disturbances from sunlight; for this reason, the custom-made stereo camera with active lighting (tiny) is the optimal choice.

Table 10 Mapping and Navigation Sensor Options

Type	***Weight (%)***	**3D LiDAR + IMU**	**2D LiDAR + IMU**	**Structured Light Camera + IMU**	**Time of Flight Camera + IMU**
Robustness	*30*	10	10	4	8
Information Richness	*30*	10	7	6	4
Low post processing	*25*	8	6	8	8
Low cost	*15*	4	6	10	8
Value		8.65	7.5	6.5	6.8

After knowing the generating the map and planned out a global path, the navigation algorithm kicks in for the robot to follow the path and avoid hitting plants/obstacles. The quality of sensors supporting the navigation algorithm/mapping is essential to the success of this task. IMU sensor is a basic sensor that presents in all option to provide information of orientation and velocity. On top of that, we compared a few aspects of the different options of range/depth sensors and weighted the values of these benefits as they pertained to our project. For example, the robustness of sensors, which corresponds to the sensors' ability to produce quality data under vibration, sun slight glare etc. Sensors that emit pulses to environment and compute distance based reflected pulses are more robustness to sun slight; the longer range that a sensor is able to work, is also captured in this criterion. Other metrics included the information richness that a sensor is able to provide (A LiDAR has a 360-degree field of view, and 3D LiDAR has additional vertical field of view on top of that). Low post processing is important for schedule to be met, the more straightforward a sensor is, it would be better. (2D LiDAR requires stitching). The cost is less of a issue since many of these sensors are available in inventory with fair amount of stock.

The 3D LiDAR is far more superior to other options in that it provides rich information and is robust to environment changes (note that we do not consider working in rainy days, where LiDAR yield poor performance). Also there are ROS packages that supports 3D LiDAR directly to make life easier.

6 Cyber-physical Architecture

The following figure shows the overall cyber-physical architecture of the robot which has been primarily divided into four components which include User Interface, Processing, Sensing and Output. The cyber-physical breakdown of each subsystem has been done below.

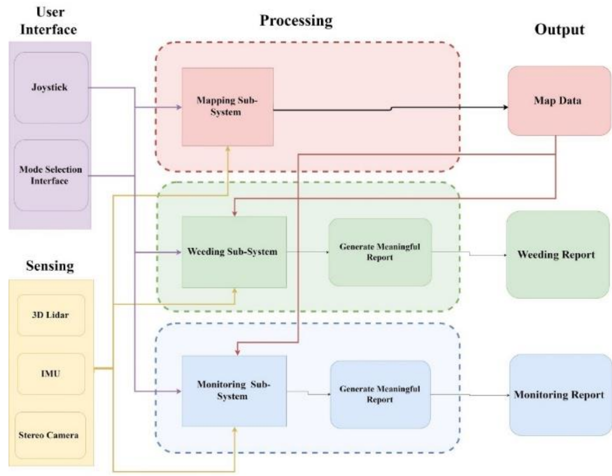

Figure 19 Overview of Cyberphysical Architecture

In mapping mode, the robot is controlled using a joystick which provides control commands which are used by the drive base controller to drive the robot's motors and move it along the desired trajectory. A 3D LIDAR and camera are used to collect point cloud and image data which is stored as a ROS Bag file. The SLAM algorithm utilizes visual and location data to generate a map of the environment.

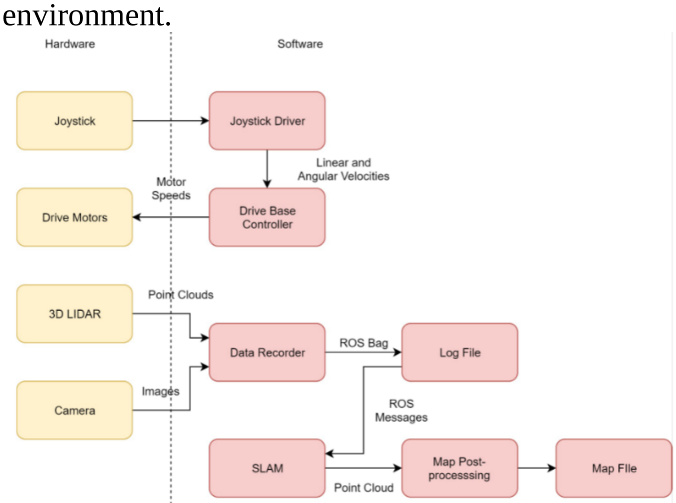

Figure 20 Cyberphysical Architecture of Mapping Mode

In monitoring mode, the robot uses a 3D LIDAR to perceive the row in which it is moving and the previously generated map file to localize itself in the row. Information from the localization algorithm is used by a high-level path planner. This path planner creates a trajectory which is utilized by the path follower which commands the robot's drive base controller to move the robot. A camera is used to collect visual data and location data for monitoring and is processed offline.

A pest/disease classification algorithm is used to detect pest/signs of disease in the images. A meaningful report is created and presented to the user in a convenient way.

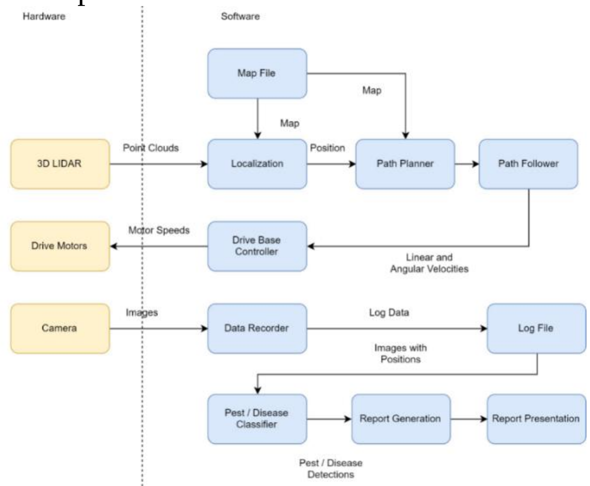

Figure 21 Cyberphysical Architecture of Monitoring Mode

In weeding mode, the robot uses a 3D LIDAR to perceive the row in which the robot is moving and the previously generated map file to localize the robot in the row. Information from the localization algorithm is used by a high-level path planner. This path planner creates a potential trajectory which is utilized by the path follower which commands the robot's drive-based controller to move the robot. A camera is used to collect visual data and location data for detecting weeds in that particular row. After the weed is detected, the 3D location of the weed in the robot frame is provided to the weeding controller. The weeding controller drives the motors of the weeding mechanism and the operation is performed. Higher level mission logic is utilized to confirm the success of the operation.

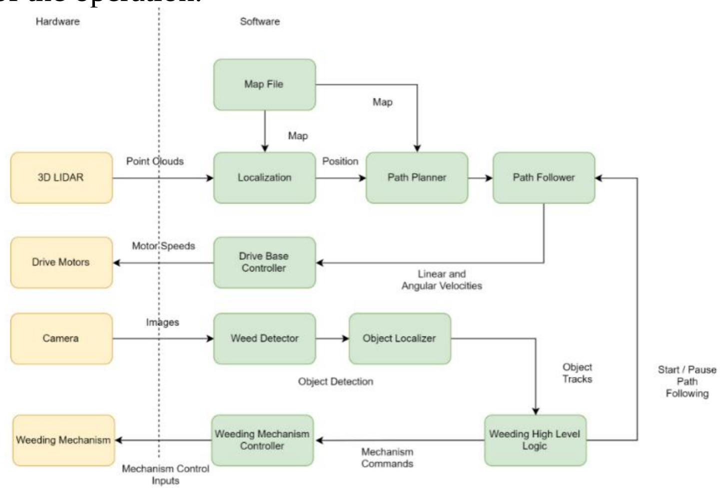

Figure 22 Cyberphysical Architecture of Weeding Mode

7 Subsystem Descriptions

7.1 Robot Platform

The robot platform consists of the hardware required for mobility of the system including hardware and software. The platform will be used to mount the sensors and the weeding mechanism and will traverse the field. The platform should have the required dimensions and dynamics to be able to traverse the brassica field with all the payload. It should also have the required computational capacity for all the tasks requiring computation and finally should have sufficient energy stored for at least one complete run of brassica field run with any of the three modes. Currently, the Robotanist is chosen as the robot platform, if this fails then we will look into using the next most suitable platform which is the Husky.

7.2 Weeding Manipulator

The 3 axes telescoping arm will work as follows. Three linear actuators (either screw threading or perpendicular gearings) will be aligned in three orthogonal directions (X, Y, Z) and configured in series. Then, knowing the relative pose of the target location, a quick transform will find the coordinates in the manipulator's frame, and the 3 axes' actuators can begin to deploy towards the plants (most likely traveling in X and Y simultaneously, and then in Z, to prevent interference with plants). An alternative version would use two revolute joints controlled by servos to control the X-Y plane, and then a linear actuator in the z-direction, holding the end effector.

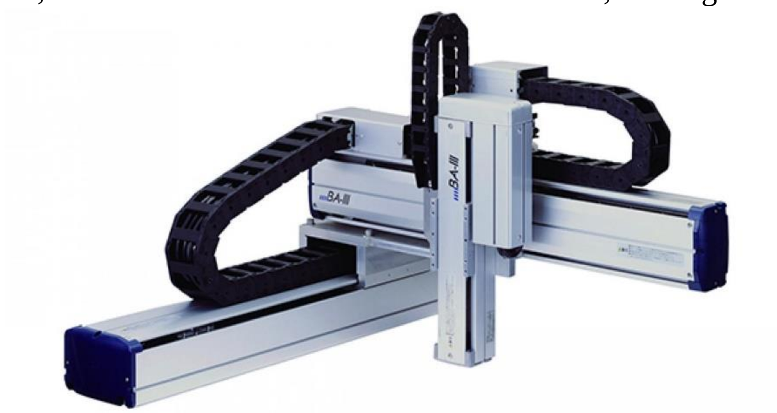

Figure 23 Example of 3-axis Telescoping Arm [12]

7.3 SLAM

The main aim of the SLAM subsystem is to capture visual data and corresponding geometric information in order to generate a map of the environment. The map could be stored as a 2D occupancy grid or a 3D Octree in order to be accessed later during autonomous navigation. In ideal conditions, the map should be efficient and robust to change in lighting conditions. The robot uses the map as a reference for precise localization and to improve the navigation performance of the system. Currently, LSD SLAM is the algorithm which has been chosen as the required SLAM algorithm. However, LSD SLAM is known to being sensitive to the incorrect initializations conditions. A hybrid sensor fusion approach using 3D LIDAR and a Monocular camera called Visual Lidar Odometry and Mapping can be used in case visual data is not enough to generate reliable maps. The ORB SLAM algorithm will be utilized if the field is able to provide rich features to create a robust map.

7.4 Perception

The monitoring perception subsystem will work as follows. The original image will be fed into a Faster RCNN algorithm for detection, which will generate bounding boxes with unique ids. The bounding boxes will be used to count the number of holes/diseased areas and they will flow into a conditioned Generative Adversarial Network for segmentation, which will quantify the size of the holes/disease on a leaf. If the subsystem is too complicated or other development tasks take priority, the fallback version is to remove the object tracker. This would sacrifice the reference to an absolute number of detected issues, which would probably be replaced by a relative metric such as the number of holes/per given area.

Figure 24 process flow of perception subsystem

The weeding perception subsystem consists of an SSD object detector architecture which predicts bounding boxes of weeds given a camera image. Depth information from the stereo camera will be combined with the bounding box to produce locations of weeds in the robot frame. If the resulting accuracy from this data-driven approach is not sufficient to achieve the performance requirements, an alternate approach would be to use graph-based image segmentation to separate weeds and ground, and then to discriminate between weed segments and other segments using a classifier such as an SVM.

7.5 Sensors

In order for our system to work reliably, a variety of sensors will be used. The specific sensor types and their purpose are described as follows. First, a ZED stereo camera will be used for localization as it provides self-computed visual odometry. Also, since outdoor environments are much more dynamic than indoors, QR code markers will be placed around over the field so that the robot can work more reliably. Second, an IMU and a 3D LiDAR sensor, will work together for navigation and avoid hitting any plants. Finally, we will use a custom-made stereo camera for the perception algorithms and localizing weeds. The camera is capable of emitting synchronized active lighting which can generate high quality, consistent data. The primary choice is the small stereo camera with casing, if that doesn't work, the alternative would be the tiny stereo camera.

Figure 25 sensors and their purposes for the system

8 Project Management

8.1 Work Plan and Tasks

The project has a large number of tasks that have to be completed. Below, the tasks are represented in terms of various major goals and their relevant subsystems. The first column represents the major goals, the next one determines the major subsystems and the third column defines the main tasks in every sub-system.

Table 11 Work Breakdown Structure

Weeding	**1.1 Weeding Mechanism**	1.1.1 Choose weeding mechanism 1.1.2 Design Mechanism End Effector 1.1.3 Design/Buy Mechanism Manipulator 1.1.4 Design Mechanism Mount 1.1.5 Fabricate End Effector 1.1.6 Fabricate Mechanism and Mounts 1.1.7 Test End Effector on field 1.1.8 Test manipulator
	1.2 Weeding Perception	1.2.1 Collect data 1.2.2 Select & train object detector to output weed bounding box 1.2.3 Select & train semantic segmentation algorithm to generate weed area 1.2.4 Compute weed location from segmentation 1.2.5 Integrate components and test end-to-end system
	1.3 Weeding Report	1.3.1 Generate heat map of weeds removed 1.3.2 Generate time history of weed spread
	1.4 Weeding Integration and Testing	1.4.1 Test combined movement of the end effector and manipulator 1.4.2 Static weeding using manual control 1.4.3 Static weeding using weed locations relative to the robot autonomously
Monitoring	**2.1 Monitoring Perception**	2.1.1 Train object detector to output weed bounding box 2.1.2 Train GAN or similar segmentation algorithm to generate weed area 2.1.3 Compute the size of holes from segmentation 2.1.4 Integrate components and test on data
	2.2 Monitoring Report	2.2.1 Generate Time History of disease 2.2.2 Generate Time History of signs of pests

	2.3 Monitoring Integration and Testing	2.3.1 Identify signs of pests and location from Visual Data 2.3.2 Identify disease and location from Visual Data 2.3.3 Test on the field and modify
Mapping	**3.1 Mapping Perception**	3.1.1 Choose map data structure (2D vs 3D) 3.1.2 Develop custom ROS package for a particular situation 3.1.3 Test mapping accuracy in a custom environment 3.1.4 Test mapping accuracy in the field
	3.2 Localisation	3.2.1 Test existing ROS localization packages 3.2.2 Develop custom ROS package for a particular situation 3.2.3 Test localization accuracy in a custom environment 3.2.4 Test localization accuracy in the field
	3.3 Mapping Testing and Integration	3.3.1 Select joystick 3.3.2 Implement / select joystick driver 3.3.3 Test basic operations. Eg: Turn left, Turn right and go straight 3.3.4 Test data collection from Sensors 3.3.5 Test map generation from collected data
Miscellaneous	**4.1 Autonomous Navigation**	4.1.1 Implement drive base controller 4.1.2 Determine drivable space / width area 4.1.3 Create a data structure for global plan 4.1.4 Generate global plan through rows (if necessary) 4.1.5 Create local path plan 4.1.6 Implement path following controller to follow the local plan 4.1.7 Implement row transition path generation 4.1.8 Test row following a performance in the field 4.1.9 Test row switching performance in the field
	4.2 Communication	4.2.1 Investigate Robotanist Wireless Communication (Inspiration) 4.2.2 Integrate wireless communication hardware 4.2.3 Setup wireless communication software 4.2.4 Test wireless communication
	4.3 System Integration and Testing	4.3.1 Purchase/assemble Robot Platform 4.3.2 Test Robot Platform -Mechanical Hardware -Robot Computation Hardware -Robot Power Supply -Mobility Performance 4.3.3 Design Sensor Mounts 4.3.4 Fabricate Sensor Mounts 4.3.5 Integrate Sensors to robot platform
	4.4 Management	4.4.1 Manage Schedule 4.4.2 Communicate with Rivendale Farms 4.4.3 Manage Finances 4.4.4 Manage Risk

The project aims to complete the Mapping and Autonomous Navigation sub-systems by spring end while developing the Monitoring and Weeding subsystem which will be delivered in the fall the exact milestones are depicted in the Gantt chart.

8.2 Schedule

During the spring semester, the primary focus will be getting the robot platform to work reliably. Hence tasks regarding the platform, such as navigation, mobility, mapping, and localization subsystems are of critical importance. These goals will be on a tight schedule since the platform is scheduled to be tested in mid-late March. Meanwhile, some other high-level goals such as the weeding manipulator and monitoring perception will be designed and developed simultaneously, but they will not be integrated until the fall semester.

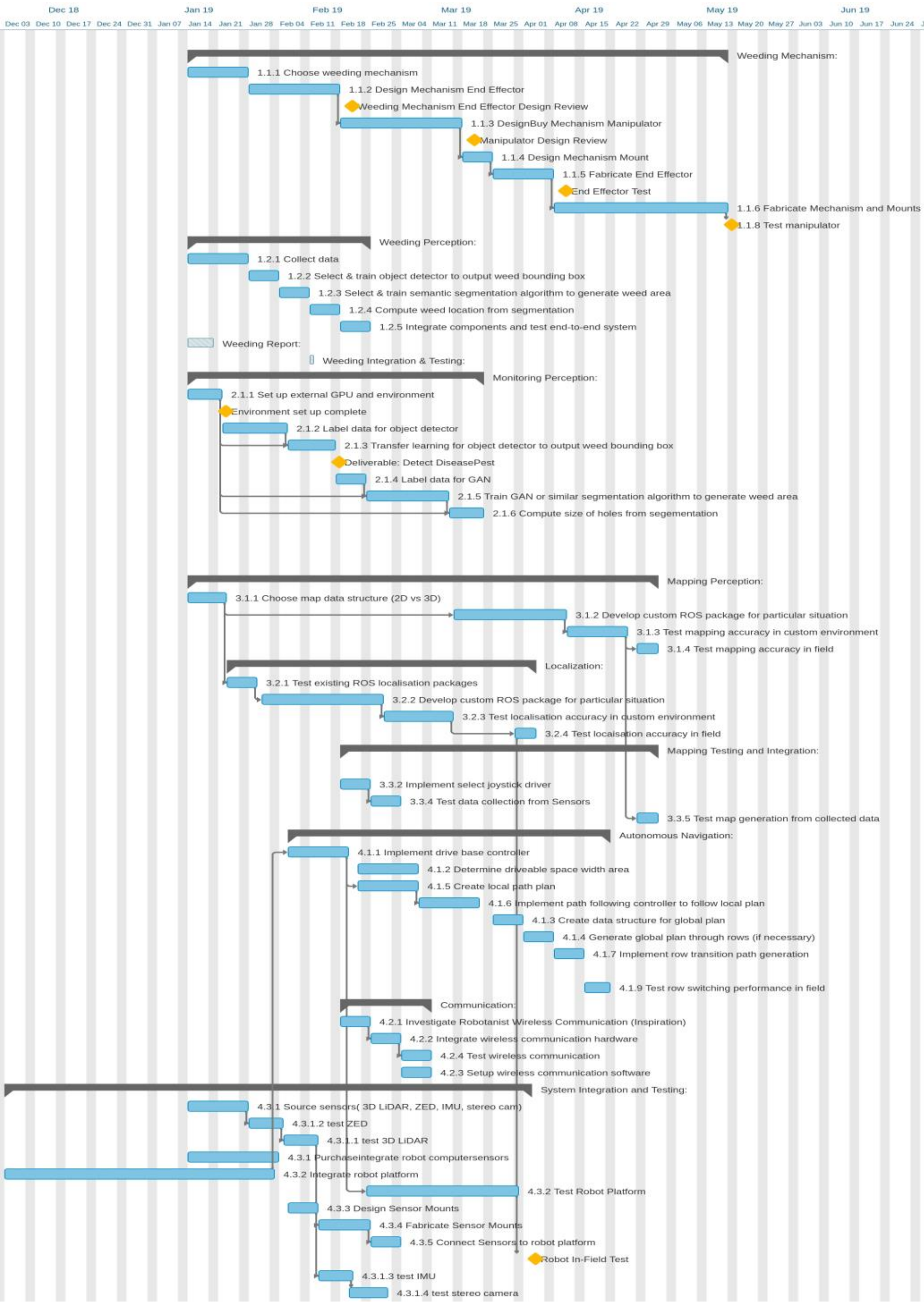

Figure 26 Gantt chart for the spring semester's work plan

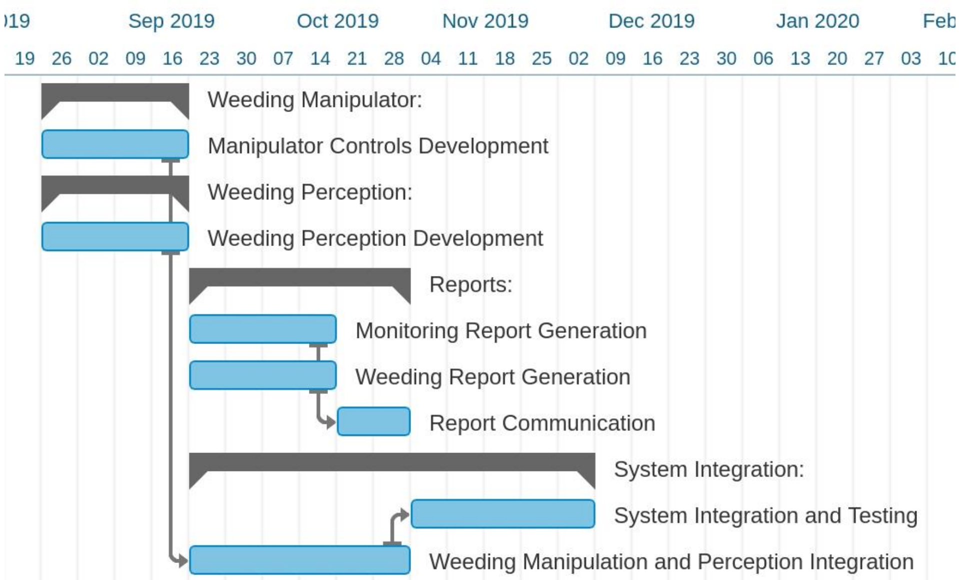

Figure 27Gantt chart for the fall semester

8.3 System Validation Experiments

8.3.1 Spring Validation Experiments

We have planned five validation tests in the spring of 2019 that are focused primarily on navigation. As such, their success criteria correspond to the navigation-related performance requirements. We have also tried to minimize the number of in-field tests required, to save on time and resources, so tests 3 through 5, which are primarily software systems, will be tested on pre-recorded data.

Test 1: In-Row Navigation

Location: Rivendale Farms
Equipment: Robot, 2 rows of plants
Setup:

- Place robot at the entrance to a row of plants, facing into the row
- Robot has pre-generated map file

Test:

1. Power on the robot
2. Establish connection to the robot
3. Command the robot to traverse the row
4. Robot navigates along the row
5. Robot stops at end of row

Success Criteria:

- Robot fits in row (MN1)
- Robot arrives at the far end of row
- Robot does not crush or trample any plants (MN5)

Test 2: Switch Row Navigation

Location: Rivendale Farms
Equipment: Robot, 3 rows of plants
Setup:

- Place robot at entrance to a row of plants, facing out of the row
- Robot has pre-generated map file

Test:

1. Power on the robot
2. Establish connection to the robot
3. Command the robot to switch rows
4. Robot navigates to the beginning of the next row
5. Robot stops at beginning of the row

Success Criteria:

- Robot arrives at the entrance to the second row in at least 4 out of 5 trials (MR5)
- Robot does not crush or trample any plants (MN5)

Test 3: Localization

Location: Rivendale Farms

Equipment: Robot, pre-recorded validation ROS Bag, localization performance measurement node

Setup:

- Load pre-recorded ROS Bag file with ground truth (from RTK GPS) onto robot

Test:

1. Power on the robot
2. Establish connection to the robot
3. Start performance measurement node
4. Playback ROS Bag file and observe divergence of ground truth and the actual position
5. Observe output of localization validation node at end of the run

Success Criteria:

- Robot is in the correct row with 95% accuracy, and within 24 inches along the row (MR4)

Test 4: Row Perception

Location: Rivendale Farms

Equipment: Robot, pre-recorded validation ROS Bag, row perception performance measurement node

Setup:

- Load pre-recorded ROS Bag file with human-labeled ground truth

Test:

1. Power on the robot
2. Establish connection to the robot
3. Start performance measurement node
4. Playback ROS Bag file and observe divergence of ground truth and actual measurement
5. Observe output of row perception validation node at end of the run

Success Criteria:

- Robot perceives drivable width of row within -10% error bound (MR3)

Test 5: Mapping Accuracy

Location: Rivendale Farms

Equipment: Robot, pre-recorded sensor data of full field traversal, manually generated map

Setup:

- Load pre-recorded ROS Bag file with human-labeled ground truth

Test:

1. Power on the robot
2. Establish connection to the robot
3. Robot generates a map using pre-recorded sensor data of full field traversal
4. Compare known location of visual markers with those of generated map

Success Criteria:

- The map has a maximum 15% dimensional error (MR2)

8.3.2 Fall Validation Experiments

Test 1: Pest/Disease Perception Test

Location: Rivendale Farms

Equipment: Robot, pre-collected and labeled dataset

Test

1. Power on the robot
2. Establish connection to the robot
3. Robot processes images and delivers a report on the number and location of plant problems (which problems will be decided later)
4. Robot report compared to labelled dataset

Success Criteria

- Robot successfully identifies problems with less than 20% false positives or false negatives (MR9, MR10)
- Robot successfully processes data at a rate faster than one field per 24 hours (MR 12)

Test 2: Weeding Perception Test

Location: Rivendale Farms

Equipment: Robot, pre-collected and labeled dataset

Test

1. Power on the robot
2. Establish connection to the robot
3. Robot processes images and delivers a report on the number and location of plant problems (which problems will be decided later)
4. Robot report compared to the labelled dataset

Success Criteria

- Robot successfully identifies weeds with false positive on plant < 5%, false negative < 30% (MR7)
- Robot successfully localizes identified weeds to positional error of <2" with respect to the robot's frame (MR8)
- Robot successfully processes data at a speed allowing for full coverage of field at robot's weeding mode speed (MR7, MR8)

Test 3: Mechanical Weeding Test

Location: Rivendale Farms

Equipment: Robot, a bed of plants with weeds present, labeled data for weed locations

Setup:

- Place robot at plant bed, with weeding manipulator facing the bed

Test

1. Power on the robot
2. Establish connection to the robot
3. Robot records plant images
4. Robot processes data online and actuates the mechanical weeder

Success Criteria

- Robot successfully removes 75% of weeds, by coverage area (MR 11)
- Robot does not damage the plant (MN 6)

Test 4: Monitoring Systems-level Test

Location: Rivendale Farms
Equipment: Robot, map file, brassica field
Setup:

- Place robot at the start of field

Test

1. Power on the robot
2. Establish connection to the robot
3. Robot autonomously navigates and localizes
4. Robot captures images of plants
5. Robot returns to the starting point
6. Robot process images
7. Robot generates and sends report

Success Criteria

- Robot does not damage plants (MN 5)
- Robot generates report in under 24 hours from completion of the test (MR12)

Test 5: Weeding Systems-level Test

Location: Rivendale Farms
Equipment: Robot, map file, 1 row of plants, human captured pictures of weeds in row
Setup:

- Place robot at the start of field

Test

1. Power on the robot
2. Establish connection to the robot
3. Robot autonomously navigates and localizes along 1 row
4. Robot captures images of plants
5. Robot process images
6. Robot Mechanically weeds field
7. Robot returns to the starting point
8. Robot generates and sends report
9. Human captured after pictures for the row are compared to before pictures

Success Criteria

- Robot does not damage plants (MN 6)
- Robot removes at least 75% of weeds by coverage area (MR 11)
- Robot generates report in under 24 hours from completion of the test (MR12)

8.4 Responsibilities

Table 12 Breakdown of Project Responsibilities

	John	Dun-Han	Hillel	Aman	Aaditya
1.1 Weeding Mechanism			1	2	
1.2 Weeding Perception	1	2			
1.3 Weeding Report	1		2		
1.4 Weeding Integration and Testing	1		1		
2.1 Monitoring Perception	2	1			2
2.2 Monitoring Report		1		2	
2.3 Monitoring Integration and Testing		1		1	
3.1 Mapping Perception		2			1
3.2 Localization	2				1
3.3 Mapping Testing and Integration				1	1
4.1 Autonomous Navigation	2			1	
4.2 Communication	1				2
4.3 System Integration and Testing			2	1	
4.4 Management	SW Schedule	Risk Management	Communication	ME Schedule	Finance

Note: 1 means ownership of the task, 2 means secondary responsibility. Tasks may have more than one "1" if the task has multiple aspects, for example, 1.4 has both hardware and software aspects, which are split between the two owners.

8.5 Parts List and Budgeting

We have not yet decided on a number of our parts, specifically the mechanical ones, as they require engineering design steps. We have ballparked a number of costs, based on our current understanding of the system and informed estimations of individual component costs. The final cost exceeds our MRSD budget, however, some of the items are in MRSD's inventory, and will, therefore, be cheaper. We also have additional funding available from both our sponsor, Rivendale Farms, and our mentor George Kantor.

Table 13 Parts List and Budget

Part	Purpose	Qty	Unit Cost	Total Cost
Velodyne Lidar 16 Beams (VLP-16)	Navigation	1	$3,999.00	$3,999.00
IMU 3DM-GX5-25	Navigation	1	$1,500.00	$1,500.00
ZED stereo camera	Localization	1	$549.00	$549.00
Vmarkers	Localization	100	$0.05	$5.00
Custom-made stereo camera	Monitor/Weeding	1	-	-
Nvidia 1080 GPU	Monitor/Weeding	1	$800.00	$800.00
Cow catcher material	not damage plant	1	$250.00	$250.00
Sensor mounting material	mount sensor			
Wifi dongle	communication	1	$25.00	$25.00

Wifi Router	communication	1	$100.00	$100.00
Robot Platform - Robotanist	Platform	1	-	-
stepper/servo motor	Weeding Manipulator	4	$250.00	$1,000.00
Metal limbs (rails, bearings, etc)	Weeding Manipulator	3	$200.00	$600.00
Weeding tooling	Weeding Manipulator	1	$200.00	$200.00

8.6 Risk Management

The process of creating the Work Breakdown Structure enabled us to identify certain critical risks which could hinder the progress of the report. Each risk has been categorized and assigned labels of **low, medium,** or **high** for both their <u>possibility</u> and their <u>impact</u> on the project. Finally, a number of mitigation steps have been proposed to resolve each risk.

Table 8 Risk management

	Risk	Risk Category	Possibility	Impact	Solution
1	Unavailability of testing locations during winter.	Scheduling Risks	High	High	Create artificial testing ground/ Utilize pre-recorded data from the farm
2	Poor weather during testing time	Scheduling Risks	Low	Medium	Avoid testing in bad weather. Implement basic waterproofing.
3	Required sensors not arriving on time	Scheduling Risks	Low	Low	Borrow sensors from Field Robotics Centre (FRC)
4	Wide scope because of monitoring and weeding	Scheduling Risks	Medium	Medium	De-scope parts of weeding/ monitoring which have a bigger impact on schedule
4	Teammates overwhelmed by school work/ assignments	Scheduling Risks	High	Medium	Schedule conservatively with adding time buffers
5	Breaking of critical sensors/ subsystems	Management/ System level Risks	Low	Medium	Borrow sensors from other teams/ Field Robotics Centre
6	Lack of communication leading to masking of critical problems with subsystems	Management/ System Level Risks	Low	Medium	Have regular stand-ups to ensure critical problems are resolved. Incorporate breakout during regular meetings
7	Lack of in-field training data for perception algorithms	Design Risks	High	High	Use GAN architecture (known to require ~100s of examples) Leverage datasets available online Use data augmentation
8	Design of weeding mechanism	Design Risks	Low	Medium	Reduce the weeding problem to simpler situations.

9	Inability to localize in the environment using pure vision	Design Risks	Low	Medium	Incorporate prior knowledge about the layout of the farm
10	Damaging plants during operations	Design Risks	Medium	High	Design safety features/ conduct an immediate review meeting

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