

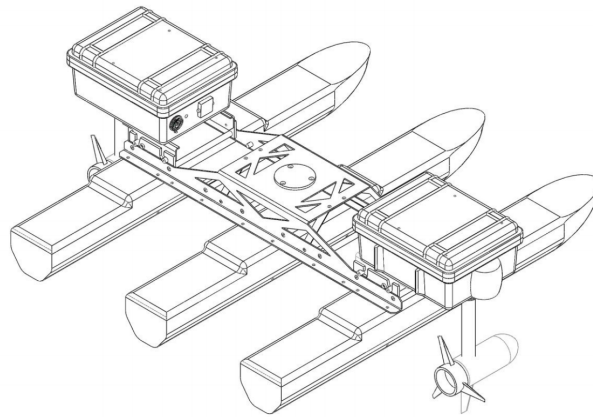
# SYSTEMS INTEGRATION OF AN AUTONOMOUS SURFACE VEHICLE UTILIZED FOR RIVER TRASH REMOVAL

ECE 4871 Senior Design Project

**Team 4 - Just Keep Swimming**

Faculty Advisor: Dr. Michael West

Corporate Sponsor: Ecolymer



**Luis Pimentel**

*B.S. in Computer Engineering*  
lpimentel3@gatech.edu

**Jin Bae**

*B.S. in Computer Engineering*  
jinbae9875@gatech.edu

**Tan Tonge**

*B.S. in Electrical Engineering*  
ttonge@gatech.edu

**Alexander Chanthaphaeng**

*B.S. in Electrical Engineering*  
asc31@gatech.edu

Georgia Institute of Technology  
School of Electrical and Computer Engineering  
Atlanta, Georgia

Spring 2021  
Submitted April 16, 2021

# Contents

<b>Contents</b>	<b>1</b>
<b>Nomenclature</b>	<b>2</b>
<b>Executive Summary</b>	<b>3</b>
<b>1 Introduction</b>	<b>4</b>
1.1 Motivation . . . . .	4
1.2 Objective . . . . .	4
1.3 Background . . . . .	5
<b>2 Project Description and Goals</b>	<b>5</b>
2.1 Sponsor and Stakeholder Requirements . . . . .	6
2.2 QFD Chart . . . . .	7
<b>3 Technical Specifications</b>	<b>7</b>
<b>4 Design Approach and Details</b>	<b>8</b>
4.1 Design Concept Ideation, Constraints, Alternatives, and Trade-offs . . . . .	8
4.1.1 Global, Economic, Environmental, and Ethical Factors . . . . .	9
4.1.2 Computation Aspects . . . . .	10
4.2 Preliminary Concept Selection . . . . .	11
4.2.1 Trash Detection . . . . .	11
4.2.2 Collision Avoidance Navigation . . . . .	12
4.2.3 Trash Localization . . . . .	14
4.2.4 Navigation to Trash . . . . .	20
4.2.5 Depth Finder / Altimeter . . . . .	20
4.3 Engineering Analysis and Experiment . . . . .	21
4.4 Codes and Standards . . . . .	22
<b>5 Schedule, Tasks, and Milestones</b>	<b>24</b>
5.1 Gantt Chart . . . . .	24
5.2 PERT Analysis . . . . .	24
<b>6 Project Demonstration</b>	<b>25</b>
<b>7 Cost Analysis</b>	<b>26</b>
<b>8 Current Status</b>	<b>28</b>
8.1 Outstanding Parts Cost . . . . .	28
<b>9 Leadership Roles</b>	<b>29</b>
<b>References</b>	<b>30</b>
<b>A Expanded Gantt Chart</b>	<b>32</b>
<b>B Expanded PERT Chart</b>	<b>35</b>

## Nomenclature

ASV — Autonomous Surface Vehicle  
DST — Digital Sonar Technology  
GPS — Global Positioning System  
LIDAR — Light Detection and Ranging  
MOOS-IvP — Mission Oriented Operating Suite Interval Programming  
PERT — Program Evaluation Review Technique  
ROS — Robot Operating System  
ROV — Remotely Operated Vehicle  
SLAM — Simultaneous Localization and Mapping  
SONAR — Sound Navigation and Ranging  
USV — Unmanned Surface Vehicle  
UTM — Universal Transverse Mercator System  
V-SLAM — Visual Simultaneous Localization and Mapping

## Executive Summary

The plastic pollution of water environments is an important problem that endangers marine animals and causes environmental issues. The goal of this project is to design a robotic Autonomous Surface Vehicle (ASV) that can collect trash within water environments such as rivers, lakes, and seas.

Currently, two systems have been implemented for this project: underwater trash detection using an underwater camera and GPS way-point navigation with collision avoidance capabilities using a laser range sensor. These systems have been implemented on a Kingfisher M100 Unmanned Surface Vehicle (USV) [1]. These systems are essential, however full autonomy is yet to be realized, as these systems are currently standalone. Complete autonomous navigation is ideal, as it allows the platform to operate without human supervision and to be deployed in varying environments. Our team's objective is to integrate the trash detection and navigation capabilities on this platform to achieve complete autonomy in these trash collection operations. Our proposed architecture connects the two existing systems through a new system whose task is to localize the detected trash in the environment and autonomously navigate the ASV to the trash's location. In order to do this we further expand the capabilities of the ASV to include visual Simultaneous Localization and Mapping (SLAM) aided by a single-beam sonar for SLAM depth correction.

Our vehicle is intended to be a proof-of-concept focused on identifying and solving the limiting problems involved with operating the ASV. The key performance specifications for this will be the ability to identify trash underwater and navigate to it while avoiding collisions with obstacles in the environment. The physical collection of the trash is outside the scope of our team's project but are challenges to be tackled by other teams. We intent to demonstrate the successful operation of this vessel on a body of water with simulated placement of plastic trash throughout.

Given the goals of this project, we are leveraging existing platforms to reduce the development cost of the vehicle. We are not focusing on delivering the most cost-effective solution as this is a proof-of-concept but are avoiding expensive technologies that would be unfeasible for a commercial solution. Next steps for future teams will include modifying the control specifically for river conditions, increased environmental mapping, and optimized path planning. Incorporating these improvements will allow the vessel to close in on reaching viability for deployment in the field.

# 1 Introduction

Our team is requesting \$663 to continue the development of a proof-of-concept autonomous surface vehicle (ASV) for robotics river plastic waste cleanup focusing on the limiting technologies involved in this challenge.

## 1.1 Motivation

Conservation of the oceans, seas, and marine resources has such a large impact on human life that it has been identified as the United Nations Sustainable Development Goal 14.1 which challenges the world to "prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities" by 2025 [2]. The world's oceans produce over half the world's oxygen and contribute to significant climate regulation as well as having an economic impact of \$282 billion in the U.S. alone [3].

If we are to prevent the pollution of these environments, we must tackle the problem at its source. River systems have a significant impact on this flow of waste as it is estimate that just 1000 rivers contribute 80% of global annual emissions up to the magnitude of 2.7 million metric tons per year with [4]. Simply implementing proper disposal methods to prevent the waste from entering rivers and oceans should fix this issue but it is found that 80 to 90% of plastic waste is improperly disposed of, primarily in low-to-middle-income income countries [5], and so we have to address the problem from a different angle.

## 1.2 Objective

The intended use of the final form of this vehicle of is to be a fully automated river cleanup system that can be deployed at strategic sections of the most relevant rivers and waterways contributing to plastic waste. This has the potential to be used by governmental and private organizations interested in the conservation of the marine environment across the world.

Primarily product functionality for this project is the removal of plastic waste from waterways in an effective manner that creates significant reduction in their impact on the marine enviroment. The vehicle must be able to accomplish these goals while operating autonomously so that minimal human input is required, therefore decreasing its operating cost and allowing for deployability at a large scale.

Significant value for the intended users is expected to either reduce a company's environmental impact through offsetting waste from their products or as a reactive measure for public and governmental organizations to eventually improve citizens health, economy, and quality of life due to the impact oceans have on all of us [3].

Autonomous vehicles are unproven in this space given the challenging environment of a moving river which can include strong currents, vessel traffic, debris, and human interference. This poses a significant

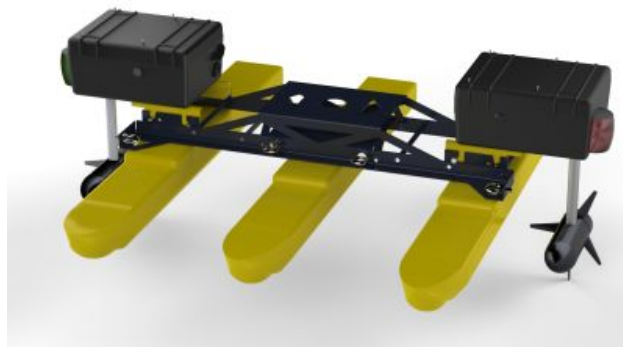
dilemma in correctly sensing the vehicles environment and navigating through it. Despite this, accurate operation is desirable as the vehicles behavior must be responsible and act with caution due to the lack of regulatory guidelines from this being a novel space.

### 1.3 Background

Interest in the space of river clean-up is increasing with potential solutions being developed by multiple groups. The Ocean Cleanup has created a collection method called "The Interceptor" which employs a stationary barrier to pull waste towards a solar powered barge with trash then being passed up by a conveyor belt into bins and has been deployed on rivers in Indonesia, Malaysia, and the Dominican Republic [4]. The Great Bubble Barrier, a Dutch startup, has installed a perforated tube laid across the bottom of a canal and then by pumping air through it creates an upward current which catches floating debris and carries them into a catchment pond [6]. Waterfront Partnership of Baltimore operates "Mr. Trash Wheel", a semi-autonomous trash interceptor that is placed at the end of a river with containment booms to funnel the trash into its gaping mouth where it is raked into a conveyor belt, which has collected over 1600 tons of debris [7].

## 2 Project Description and Goals

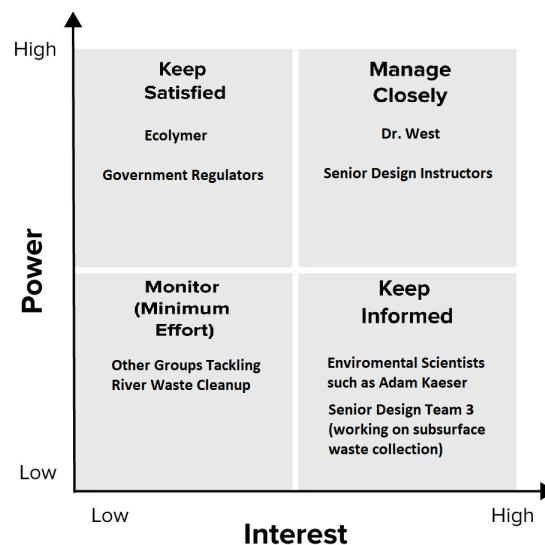
The Kingfisher M100 [1] provided by Dr.West has been identified as the proof-of-concept platform to eliminate development time on a USV when several suitable platforms such as this one already exist. We will be integrating the collision avoidance and object identification methods performed by previous teams onto the USV. Then we will be adding a forward-facing sonar to pinpoint the plastic in front of the vehicle under the surface of the water and navigate to it. We will then have a stretch goal of developing global path planning around the body of water by adding a second downward-facing depth finder to serve as edge detection to prevent beaching.



**Figure 1:** Kingfisher M100 base platform from Clearpath Robotics Inc. [1].

## 2.1 Sponsor and Stakeholder Requirements

**Sponsor Description** Ecolymer has sponsored the development of this Senior Design project. Ecolymer is a worldwide plastic packaging producer based in Austria with around 20,800 employees at 178 locations across 46 countries leading to its place as a market leader for brands in the food, beverage, pharmaceutical, oil and lubricant, home, and beauty care industries. As a family-owned company, they are aware that their social responsibility to their employees, customers, and the environment should characterize their way of thinking and working worldwide [8].



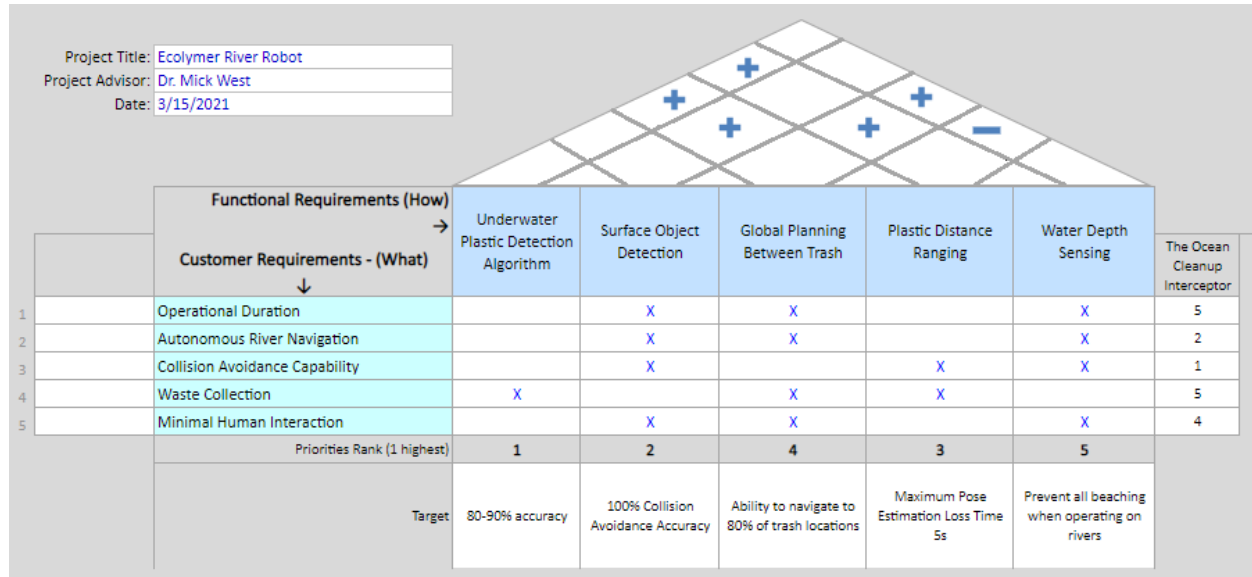
**Figure 2:** Stakeholder "2x2" chart comparing interest and power in this project.

**Customer Needs** Ecolymer desires a fully automated river clean-up system that can be deployed in waterways to identify, collect, and dispose of plastic waste without interfering with river traffic or aquatic life. Once the garbage is collected, it can then either be re-purposed through recycling or it can be used locally to generate electricity through incineration. They are searching for a solution that is reasonably priced so that its deployment would be economically viable at a large scale. They are fairly flexible in our approach and methods to tackling this problem as they are primarily looking for a prototype system which proves the operational ability of the underlying technologies.

We must also strictly meet the requirements of the Senior Design instructors in our development process so that we are successful in the project deliverables associated with this course. These include the final report and Capstone Expo presentation. Finally, we have also made contact with some environmental scientists in our research for this project. Adam J. Kaeser, an aquatic ecologist with the U.S. Fish and Wildlife Service,

was particularly interested in our project and the impact it could have on the environmental mapping and habitat classification of inland waterways through sonar equipment in addition to the primary goals. We also expect to maintain communication with the other Senior Design team working on this problem but tackling it from the angle of subsurface waste collection by leveraging an ROV.

## 2.2 QFD Chart



**Figure 3:** Quality Function Deployment Chart Based on Customer Needs and Engineering Requirements.

## 3 Technical Specifications

Qualitative Specifications
Ability to detect trash objects using camera system and pre-trained trash detection model
Ability to localize trash detected in the robot's image frame using algorithm
Ability to navigate robot from a starting point to a trash location

**Table 1:** Qualitative Design Specifications for Autonomous Operation.



Quantitative Specifications	
Plastic Detection Accuracy	80-90%
Plastic Detection Range	0.3m-5.0m
Collision Avoidance Accuracy	100%
Collision Avoidance Time	25-50% of original trajectory time
Sonar Map Depth Correction Range	5.0m
Maximum Feature Tracking Loss Time	15 s
Maximum Pose Estimation Loss Time	5 s

**Table 2:** Quantitative Design Specifications for Simulated Waste Cleanup.

## 4 Design Approach and Details

### 4.1 Design Concept Ideation, Constraints, Alternatives, and Trade-offs

Most significantly, we must consider the feasible time and scope of this project during a single semester as the final goal of an autonomous surface vehicle is quite extensive. Therefore, we are continuing this ongoing project from past semesters and will focus on the integration of past software work using the existing Kingfisher M100 platform to achieve the full goal. This will allow us to accomplish a reasonable goal without spending much time on mechanical design or the details of already completed work.

Secondly, we are limited on the cost of sensors for environment perception. Given a larger budget, we could purchase expensive lidar or bathymetry sensors that would allow for increased levels of autonomy in mapping path planning. Due to this we must develop smarter ways of sensing the robot's environment to influence these navigation decisions.

The most significant trade-offs for the project are budget and the time and technical skills required for the implementation of the project. It would certainly increase the performance of the robot if expensive sensors are used for localization. For instance, using \$4000 Velodyne VLP16 instead of a Microsoft Kinect would provide a point cloud that covers 360 degrees around the robot with much longer coverage compared to Kinect. As for the skills and time required for the project, it is impossible to implement features such as underwater sonar due to the complexity of the task and the price of the components that are priced outside of the budget. The solution is to use hardware that is within the project budget and implement features within our skillsets.

The following tables summarize comparisons between different sensors that were considered:

Camera Comparison					
Camera	FOV (H/V)	Max-Resolution	Streaming	Waterproof	Price
Low-Light HD USB Camera	80/64°	1920x1080	USB	No	\$99
Blackfly S USB3	N/A	1440×1080	USB	No	\$335
GoPro HERO4	122/94°	4K	Wi-Fi	Yes	\$399
DTPod Underwater Camera	360°	1920x1080	USB	Yes	\$5198

**Table 3:** Camera sensor comparison of specifications considered.

Sonar Comparison				
Sonar	FOV (degree)	Range (m)	Data Interface	Price
Ping Sonar Altimeter and Echosounder	30°	30	UART/Serial	\$279.00
Tritech Micron EchoSounder	6°	50	UART/Serial	\$1995.00
Ping360 Scanning Imaging Sonar	360°	50	UART/Serial	\$1975.00

**Table 4:** Sonar sensor comparison of specifications considered.

#### 4.1.1 Global, Economic, Environmental, and Ethical Factors

Human activity results in about eight million tons of plastics entering the ocean every year [4]. When plastics enter the ocean, it does immeasurable damage not only to the ocean wild life but also to the global population that consume food harvested from the ocean. Apart from the usual publicly televised suffocation and entanglement of wild life, the ocean currents and winds degrade the plastics into smaller pieces until they are considered to be microplastics with lengths less than five millimeters [9]. Microplastics are consumed by many wild life that include sea harvests consumed by humans. This raises a serious health concern since there are rising studies that suggest toxicity and epidemiology related to microplastic [9]. This project is aimed at alleviating the global marine plastic crisis by exploiting the developing areas of robotics and artificial intelligence, thus positively contributing to the global health, environment, and sustainability, effectively automating the ethical dilemma of marine pollution.

There are potential concerns regarding the ethical aspects of the project. One concern is the possibility of the ASV harming the wild life by accidentally injuring them with mechanical parts. As a relevant example, at least 136 manatees in Florida were killed by boats in 2019 [10]. However, this problem is addressed in two parts in this project. Firstly, any sufficiently large objects, whether that be a marine animal or a rock, will be considered an obstacle by the obstacle avoidance system implemented with MOOS-ivp. Also, the YOLO v2 object detection system includes the 'marine-life' class and makes the robot carry out conscious maneuvers not to engage with marine wild life. Another concern might be that the robot might get involved in a collision accident with other vehicles, but this is also addressed by adding the 'remotely-operated-vehicle' class in the detection system.

This project is intended to provide a cheaper alternative to hiring laborers or relying on volunteers to reduce marine plastic. The cumulative development cost of the project prototype is expected to be expensive,

but the mass production and mass deployment of these robots will likely prove to be cheaper and easier than relying on human labor. In addition, these robots will also be able to operate in environments that could be dangerous to humans, providing an ethical relief.

As for the political factors, the design of the robot abides by the codes and laws issued by the government of the region the robot is operating in which is discussed in the Codes and Standards section.

#### 4.1.2 Computation Aspects

The river robot will carry an on-board Jetson TX2 for computation. This computer will interface with the onboard hardware sensors in order to process the data that is used in the algorithms for trash detection, collision avoidance, and path planning. The Kinect RGB-D sensor provides image and depth data that will be used to detect and localize potential trash targets in the environment. The range for this sensor is 0.5 - 5 meters and its performance is heavily dependent on the lighting conditions of the environment. GPS and IMU sensors will be used to localize the robot in its environment and for the path planning algorithm to generate GPS waypoints from the robot's location to potential trash targets. GPS performance can be impacted by weather conditions. The algorithms developed will interface with MOOS, an open source USV autonomy stack that will implement physical control of the robot.

The communication between our main software and the sensors will be done on a platform called Robot Operating System (ROS). ROS is a over-the-network middle ware that allows different ROS scripts called nodes to communicate with each other through channels called topics and services. The manufacturers of devices frequently used for robotic applications, such as Kinect, IMU, and GPS, provide their open source ROS packages that allow users to interface their devices with their software. In addition, many useful ROS robotics navigation packages such as the navigation stack and robot localization are available for use. However, since the previous team decided to implement the GPS waypoint navigation in MOOS, only robot localization package will be used to implement the Kalman filters required for frame transformations. Running two middle wares such as MOOS and ROS could be heavy, but it is a necessary decision since there aren't any sensor drivers available on MOOS. ROS also allows for over-the-network communication which is needed in this project for the manual control of the robot using a tele-op package called teleop\_twist\_joy, yet another ROS package.

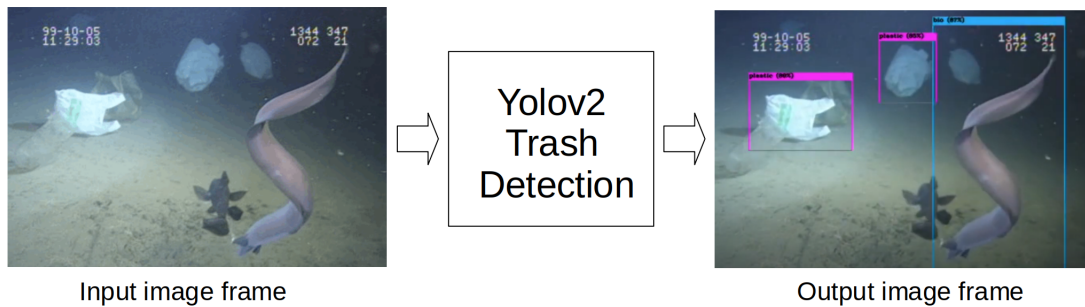
The entire project can be implemented by using ROS as the sole middle ware and significantly lighten the computational load. However, MOOS is specialized for autonomous marine systems and has the ability to carry out maneuvers such as varying motor speeds in response to the erratic aquatic environment. This allows the robot to be deployed not only in isolated bodies of water but also rivers and ocean where the robot might be exposed to strong currents.

## 4.2 Preliminary Concept Selection

In this section, we detail the technical systems previously implemented by former teams for trash detection and collision-avoidance navigation. Furthermore, we detail our additions to these systems and our novel system for localizing the detected trash in the robot's environment in order to autonomously navigate the Kingfisher to the trash's location.

### 4.2.1 Trash Detection

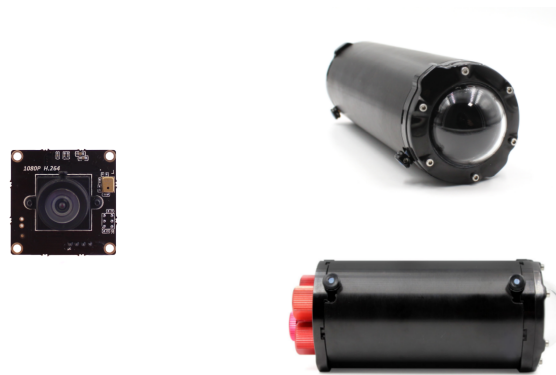
The Fall 2020 team implemented a trash detection system on that was able to detect trash within an image frame. To do this, a real-time object detection system called YOLOv2 [11] is used. This system uses a neural network architecture with an object detection model that has been trained on a ocean trash data-set of over 5700 images [12] to detect three classes of objects: “plastic”, “marine-life”, and “remotely-operated vehicle (ROV)”. This objection detection system has the ability to take in as input a video stream and outputs the video's current processed image frame with a rectangular bounding box encapsulating the area of pixels that contain the detected object along with a confidence measure.



**Figure 4:** Input image frame to the YoloV2 detection system and corresponding output with bounding boxes around the detected objects. Input image is from the Trash-ICRA19 dataset.

While the Fall 2020 team managed to train the detection model and run successful object detection experiments on a validation set, our project proposes continuing their work by integrating this system on-board to the Kingfisher robot with a live-video input feed to the detection system. We consider the previous team's challenges in integrating an underwater Go-Pro Hero 4 camera, mainly that the camera's only image streaming capability consisted of a wireless connection that was unable to successfully connect to the Jetson TX2. We further consider challenges that wireless streaming of images may cause such as signal interference due to a underwater camera operation, and image streaming lag issues that may make it unfeasible to run the trash detection and localization algorithms in real time.

Our team proposes using a monocular camera with a USB interface in order to eliminate previous issues with wireless streaming, and interface with standard image streaming libraries. We select the Blue Robotics Low-Light HD USB Camera for its low-cost, superior performance in low-light environments, and its proven use in underwater ROV applications [13]. In order to use this camera underwater, we must consider how to eliminate damage to the camera's electronics and electrical wiring. We select to install this camera within a Blue Robotics cylindrical Watertight Enclosure with a 50mm diameter and 100 mm length capable of holding our camera and providing a water-tight USB cable interface to our on-board computer [14]. This enclosure will be rigidly mounted under the robot with the camera facing forwards.



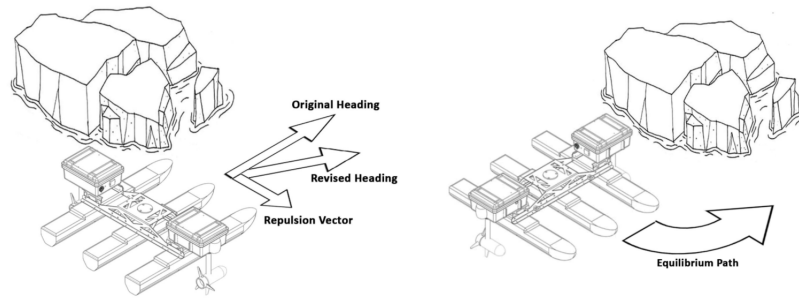
**Figure 5:** Low-Light HD USB Camera (left) [13] and cylindrical Watertight Enclosure (right) [14] to be integrated as the new physical camera system. Objects not to relative scale.

With this hardware installed successfully, we will be able to extract the camera's live video stream through standard ROS libraries for USB camera drivers and camera calibration software[15, 16]. Processing our video through ROS will easily allow us to redirect our image stream to multiple software modules running on the robot including our trash detection and trash localization software.

#### 4.2.2 Collision Avoidance Navigation

The Spring 2021 team has implemented GPS way-point navigation capabilities on the Kingfisher robot through the use of MOOS-IvP, an open source library with autonomy capabilities for marine vehicles [17]. Furthermore, the team has added capabilities for detecting and avoiding surface obstacles through the use of Kinect v2 Infra-Red (IR) laser sensor atop the robot. Their algorithm implements a potential-field local planning algorithm that allows the Kingfisher to navigate around obstacles and resume its route to pre-programmed GPS way-points.

Our team proposes leveraging this architecture and extending its capabilities to be completely autonomous. Rather than manually inputting GPS way-points, we propose autonomously generating the



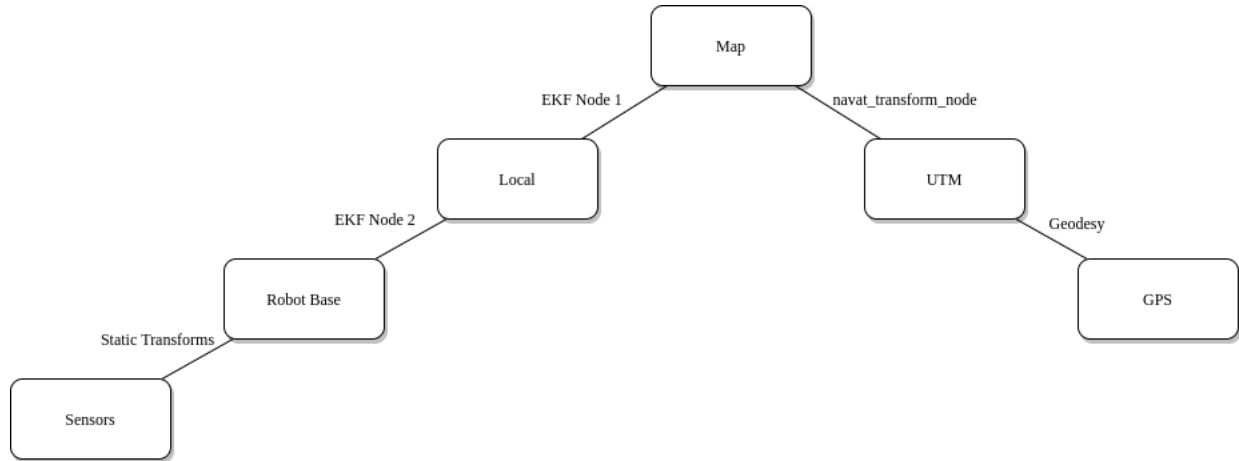
**Figure 6:** Diagram of Kingfisher implementing its collision avoidance algorithm.

GPS way-point destinations through our trash localization architecture. This architecture will output the 3D spatial coordinates of the detected trash relative to the Kingfisher robot's local frame. These 3D coordinates will be projected to 2D GPS way-points in the robot's global frame. These 2D GPS way-points will be automatically passed on to the navigation architecture in order to navigate the Kingfisher to the detected trash's location with the collision avoidance capabilities ensuring that the robot reaches its goal safely and autonomously.

Global Positioning System (GPS) is a crucial source of position estimation for outdoor robots since data from the odometer constantly drift from the actual position. This is especially true when applied to Autonomous Surface Vessels (ASV) as the erratic nature of aquatic environments introduces significant noise to local sensors. The longitude and latitude data received from the GPS module are first converted to a frame called the Universal Transverse Mercator (UTM) coordinate system. The UTM system is a system of assigning Cartesian coordinates to different locations on the Earth by dividing the Earth into 60 zones and projecting each with an X-Y plane. This makes defining a global location possible by selecting the zone and the Cartesian coordinates in that plane. Once the GPS data have been converted to the UTM frame, it is just a matter of linear translation to transform the location data into the local frame. The transformation tree structure will be as follows:

Once the trash location within the local frame is acquired, the transformation tree structure can be used to transform the location into the UTM frame which could then be converted to a GPS coordinate for GPS waypoint navigation.

The previous team implemented the GPS waypoint navigation by relying on GPS as the only source of position for the robot without performing state estimation. However, it is necessary to fuse GPS coordinates with position information from other sensors such as an IMU in order to localize trash within a known frame. This can be achieved by the use of state estimation models such as Kalman filter. Kalman filter takes in



**Figure 7:** Frame transformation tree.

position data from multiple sources and outputs the best estimate of the robot's position based on how much weight is applied to each source's data. The reliance on a certain source can be decreased by increasing the values in the noise covariance matrix for that particular sensor. Since local sensors such as odometry and IMU are known to introduce a constant drift from the accurate position, the noise covariance values can be increased for the local sensors in order to allow the GPS data to correct for the drift reliably.

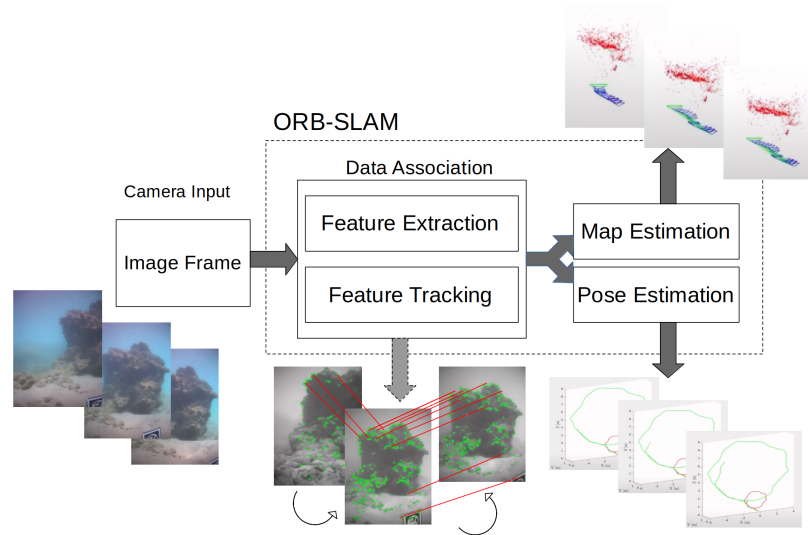
#### 4.2.3 Trash Localization

In this section, we detail our novel architecture for localizing the detected trash in the robot's environment. Currently, the trash detection system is able to localize the trash within the camera's image frame through a bounding box that encapsulates our detected trash. However, this does not give us any spatial information regarding the actual locations of the trash in the robot's environment. The capability to extract this information is essential if we wish to deploy fully autonomous operation.

We propose an architecture that leverages our current use of a monocular camera as our main underwater sensor on this platform. We will implement a Visual Simultaneous Localization and Mapping (V-SLAM) library that will allow us to localize the robot using underwater visual information and simultaneously create a 3D map of the environment the robot is navigating. Furthermore, we enhance the capabilities of this monocular V-SLAM library by fusing depth information using a single-beam echo-sounder sonar sensor. Having successfully implemented these capabilities, we will be able to map 3D points representing spatial features of objects within the camera and sonar's range. We can then use our trash detection system to filter out 3D feature points that belong to the detected trash. Using these points we can then estimate the 3D location of the detected trash and allow the robot to navigate towards these locations. In the next few sections, we detail the technologies and processes involved in this architecture.

**ORB-SLAM2** Our primary motivation for using V-SLAM is to utilize its visual and spatial feature extraction capabilities to estimate the 3D position of the detected trash. We do this by utilizing V-SLAM’s capabilities to map detected feature points

We selected a standard open-source V-SLAM library called ORB-SLAM2 for its proven ability to work in real-time systems and in varying environments [18, 19]. Furthermore, ORB-SLAM2 has been previously used in underwater applications with promising results [20, 21, 22]. In the next section, we detail a monocular depth scale correction method using sonar range measurements that been used exclusively with the ORB-SLAM2 library. This is a development that we hope to leverage in our work.



**Figure 8:** Diagram detailing the simplified main components of the ORB-SLAM architecture. The images used for visualization purposes belong to the following experimental results [23].

In Figure 8, we detail the main components of the ORB-SLAM architecture. Our following overview is highly simplified and we encourage further reading of the original cited papers.

- **Image Frame Input:** live image-stream from a monocular camera is input to the ORB-SLAM system as the robot moves in the environment with the camera rigidly attached.
- **Data Association**
  - **Feature Extraction:** interest points corresponding to ORB descriptors, feature vector representations of the interest point, are extracted from image frames. Common interest points include corners and edge-like regions in an image.
  - **Feature Tracking:** given the extracted features and feature descriptors, these points are matched correspondingly across image frames and tracked by computing the corresponding transformations



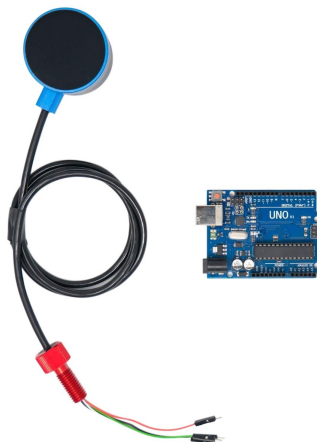
between image frames. These transformations are used to estimate a map of the robot's environment and its pose.

- **Map Estimation:** extracted features in the image frame are projected in the 3D world relative to the robot according the computed transformations forming a point-cloud map.
- **Pose Estimation:** the pose of the robot is estimated using the computed transformations between image frames.

ORB-SLAM2 works best when used with a stereo or RGB-D camera providing accurate depth information. When used with a low-cost monocular camera like the one used in our robot, the scale of the map and the estimated pose of the robot is ambiguous due to a lack of depth information that cannot be provided with a single camera. In the next part, we detail a method our team proposes to use in order to resolve these scale ambiguity issues by adding depth information through a sonar sensor.

**Depth-Correction using an Echosounder Sonar** In order to solve for scale ambiguity issues of monocular V-SLAM, we propose installing a forward facing sonar which provides range measurements used to offer scale information of the features extracted in the camera's image frame in the ORB-SLAM architecture, as is done in work by the Dartmouth Reality and Robotics Lab [24]. We use the same Blue Robotics single-beam Echosounder sonar [25] as used in this work due the ability to use their calibration software, easing development time [26]. Furthermore, Blue Robotics provides an open-source Arduino interface [27] for extracting sensor measurements. Our team will integrate this into our software stack on-board the robot.

In the following, we provide a brief overview of the echosounder model and how it is integrated with ORB-SLAM for depth correction.



**Figure 9:** Blue Robotics Ping Sonar Echosounder [25] with Arduino Uno micro-controller interface [28].

The echosounder is able to obtain a depth measurement  $m_i$  by emitting an acoustic pulse into the environment and measuring the time-of-flight  $t_i$  as the pulse is reflected in a water environment with sound velocity  $v$ , such that:

$$m_i = v \cdot \left( \frac{t_i}{2} \right) \quad (1)$$

$$d_0 \leq m_i \leq d_{max} \quad (2)$$

where (2) denotes the range of the echosounder. The propagation of the pulse can be modeled as a cone whose circular base can be projected on to the camera's image frame given the echosounder and camera intrinsic parameters:

- ${}_C\mathbf{t}_E$ : Echosounder position with respect to the camera frame.
- $\vec{\mathbf{v}}$ : Echosounder direction vector.
- $\alpha$ : Echosounder cone angle.
- $K$ : pinhole camera intrinsic parameter matrix.

The echosounder parameters will be calibrated using the ESCalibr [26] library and the camera will be calibrated using the camera\_calibration library [16]. Given these parameters, we can calculate the circle's center  ${}_C\mathbf{c}_i$  with respect to the camera frame with a circle radius  $r_i$  as:

$${}_C\mathbf{c}_i = {}_C\mathbf{t}_E + m_i \cdot \vec{\mathbf{v}} \quad (3)$$

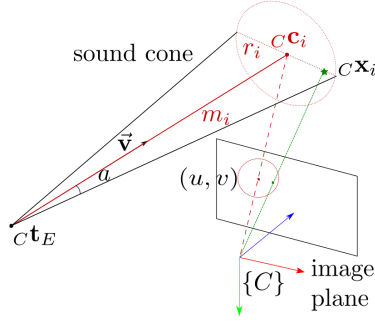
$$r_i = m_i \cdot \tan(\alpha) \quad (4)$$

We then project the circle's center on to the image frame:

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K \cdot {}_C\mathbf{c}_i \quad (5)$$

obtaining the pixel coordinates  $(u, v)$  of the circle in the image frame.

This model is used to correct depth estimates of feature points extracted and mapped by ORB-SLAM, which would otherwise be incorrect due to scale ambiguity of monocular V-SLAM. The depth correction algorithm presented takes into account extracted feature points  $f_j$  whose pixels are within this projected circle, with corresponding 3D map points  $\{{}_W\mathbf{x}_s \in F_v\}$ . The new depth estimate  $d_m$  is calculated by solving



**Figure 10:** Echosounder-camera model showing how the sonar measurements are projected on to the camera's image frame as presented in [24].

a least optimization problem that minimizes the residual between the 3D position of the feature point  ${}_W\mathbf{x}_s$  along the camera's line of view, with camera pose  ${}_C\mathbf{T}_W$ , and the echosounder's measurement.

$$d_m = \operatorname{argmin}_{{}_W\mathbf{x}_s} \left( \left\| {}_C\mathbf{T}_W \cdot [{}_W\mathbf{x}_s^T \ 1]^T - [{}_C\mathbf{t}_E^T \ 1]^T \right\| - m_i \right)^2 \quad (6)$$

Given this, a depth correction ratio  $d_i$  is calculated using these depth estimates to adjust both the mapped feature points and the pose of the robot:

$$d_i = \frac{d_m}{\|{}_W\mathbf{x}_s - {}_W\mathbf{t}_E^C\|} \quad (7)$$

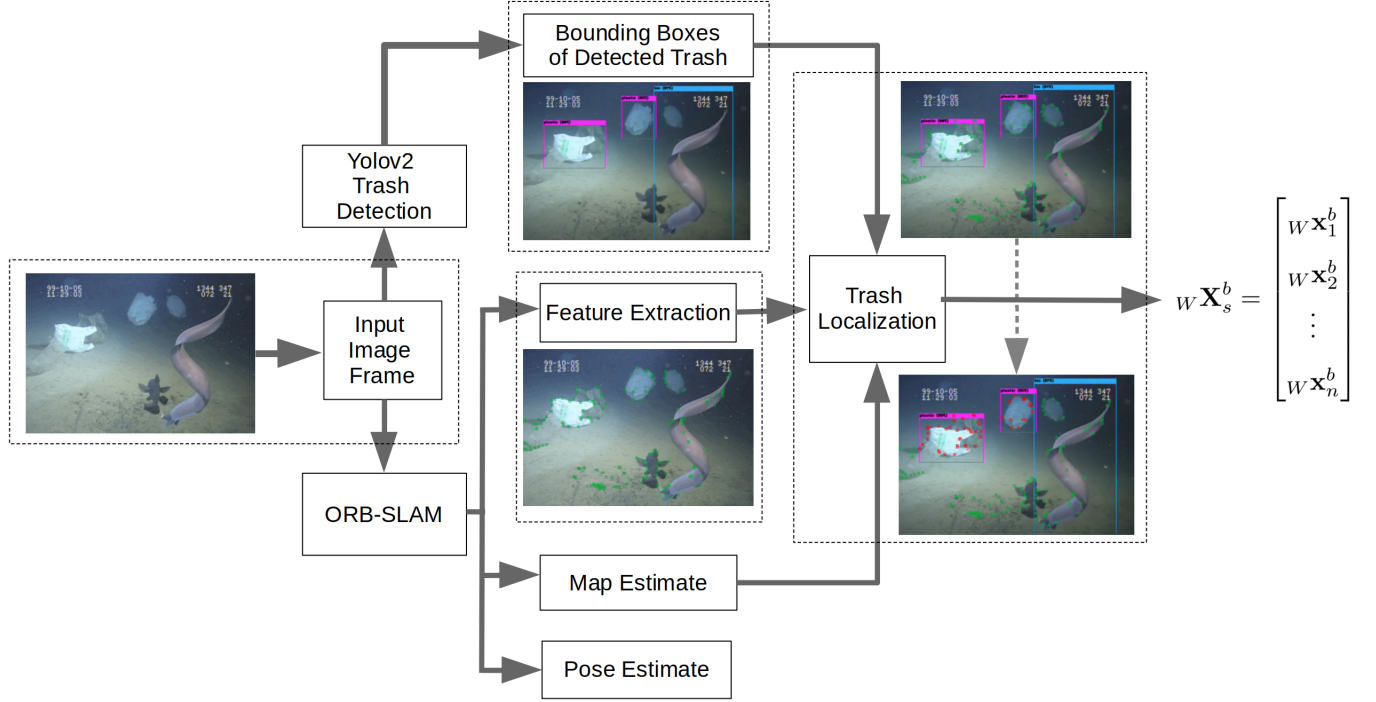
This depth correction method is implemented inside of the ORB-SLAM feature tracking pipeline. Using this modified ORB-SLAM architecture, we are able to produce accurate 3D map points corresponding to features extracted in the camera's image frame. Furthermore, we can obtain an accurate 3D pose of our robot as it is navigating.

**Trash Localization Pipeline** In this section, we detail how we will use the depth corrected 3D map points generated by ORB-SLAM to localize our detected trash. In our architecture we input the same camera live image-stream to both the trash detection system and the ORB-SLAM system.

When the trash detection system is able to detect trash within the image frame it will output a rectangular bounding box around the pixel locations localizing the trash inside the image frame as described in section 4.2.1. Here we consider the general case where the detector outputs one or multiple  $k$  bounding boxes around  $k$  detected trash objects. We denote the bounding boxes as  $B_k \in \{B_1, B_2, \dots, B_k\}$ . Next, we consider the feature points in the image frame (pixel coordinates) extracted and tracked by ORB-SLAM denoted as  $f_e$ . These feature points will have corresponding 3D map points denoted as  $\{{}_W\mathbf{x}_s^e \in F_e\}$ .

We use the bounding boxes  $B_k$  output by the detection system to filter out any feature points that do

not belong to detected trash objects. We do this by only considering the subset of feature points in the image frame that are inside of  $B_k$ . We denote this subset as  $f_b \subseteq f_e$  and the corresponding 3D map points as  $\{w\mathbf{x}_s^b \in F_b \subseteq F_e\}$ . Using this subset we create an array  $w\mathbf{X}_s^b$  which contains all of the 3D map points that belong to extracted features of the detected trash objects in the image frame.



**Figure 11:** The proposed trash localization architecture with input/output image frames next to intermediate processes. These image frames are from the Trash-ICRA19 dataset [12] and are edited to show expected feature points output from ORB-SLAM and processed through our trash localization system. The bottom right image frame shows all of the tracked feature points (green) and the feature points that belong to the trash (red) with labeled bounding boxes over detected objects.  $w\mathbf{X}_s^b$  denotes the 3D points of all features belonging to trash.

The 3D points in  $w\mathbf{X}_s^b$  do not yet contain any association to the particular trash they belong to. Furthermore, in order to create a GPS way-point that the robot can navigate we need to represent the trash locations with a single 3D coordinate point. In order to do this, we use a K-means clustering method that partitions the  $N$  3D points into  $K$  ( $\leq N$ ) sets  $\mathcal{C} = \{\mathcal{C}_k\}_{k=1}^K$ , where we set  $K$  equal to the number of bounding boxes detecting trash in the image frame. We assign a point to a cluster  $\mathcal{C}_k$  such that the point's distance to that cluster's center  $u_k$  is minimum over all other clusters. To do this, we initialize  $u_k$  cluster centers to  $K$  random points in the set  $w\mathbf{X}_s^b$ . This formulation can be represented as solving the following optimization

problem:

$$\underset{\mathcal{C}}{\operatorname{argmin}} \sum_{k=1}^K \sum_{w \mathbf{x}_s^b \in \mathcal{C}_k} \|w \mathbf{x}_s^b - u_k\|_2^2 \quad (8)$$

At each iteration, after assignment, the cluster centers  $u_k$  are recomputed based on new assignments such that:

$$u_k = \frac{1}{|\mathcal{C}_k|} \left( \sum_{w \mathbf{x}_s^b \in \mathcal{C}_k} w \mathbf{x}_s^b \right) \quad (9)$$

Where  $|\mathcal{C}_k|$  represents the total number of points in that cluster. We use these  $K$  cluster centers in order to represent the  $K$  trash locations detected.

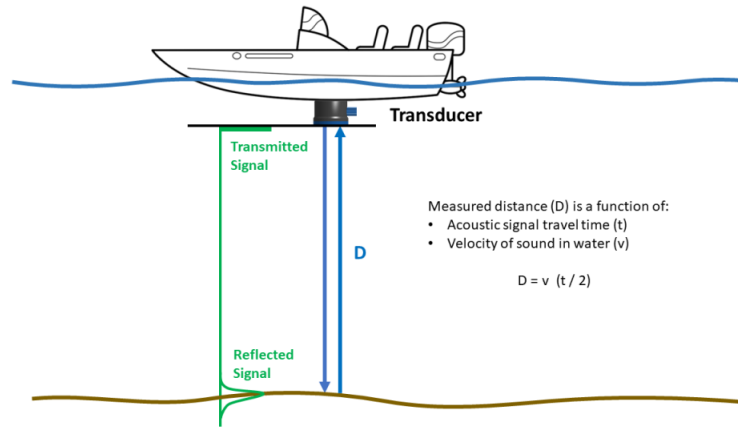
This K-mean clustering formulation is advantageous as it allows us to distinguish between objects whose bounding boxes (therefore considered features) are overlapping. This can also prove to be useful in eliminating noise from outlier points. Furthermore, though out of the scope of this project, statistical analysis can be implemented in this formulation taking into account the probability levels of the trash detector on the given feature point.

#### 4.2.4 Navigation to Trash

The execution of ORB-SLAM will produce a pose estimate of the target trash in the map frame. Since only the X-Y plane coordinate is required for the conversion to the UTM frame, the depth value can be effectively ignored for the purpose of generating a GPS waypoint. Once the GPS coordinate for the trash has been acquired by using the transformation tree, it can be fed into the GPS waypoint navigation software developed by the preceding team. Assuming that the GPS module can maintain a fix and the precision is within a reasonable range, the GPS waypoint navigation will bring the robot right above the target trash. The objective for this team is to automate the trash detection and navigation portion of the robot's operation, therefore we won't be implementing the actual collection of the trash and leave that to the future team with more members with more expertise in mechanical engineering. Once the robot has reached the target location, it will return to searching for the next target trash.

#### 4.2.5 Depth Finder / Altimeter

As a stretch goal we propose further enhancing autonomy capabilities through sonar sensing modalities. We propose implementing a downward-facing Tritech Micron Echosounder [29] which utilizes Digital Sonar Technology (DST) to provide a water depth value to in order to create an underwater depth map that can



**Figure 12:** Echosounder/altimeter operating principle from [27].

inform a path planning algorithm when operating on a river or a lake. The operation of this is shown in Figure 12 and described by Equation 1 through measuring the time between the acoustic signal being emitted by the transducer, reflecting off the river floor, and being received by the sensor. It is important to use a different echosounder than established in Section 4.2.3 to prevent interference from these two devices operating simultaneously. As the BlueRobotics echosounder operates at 115 kHz and the Tritech Micron Echosounder operates at 500 kHz, this should not be an issue. This device has a range of 50 meters which will provide plenty of margin for the environments the vehicle is intended to operate in.

This will allow us to judge the banks of the river much better than a surface-mounted sensor such as the Kinect to establish the boundaries of the operating space. This will prevent the vehicle from becoming beached on the banks or other shallow areas and therefore require human intervention for recovery. As this is a final step towards implementing full autonomous operations, this is a low priority goal for the Fall 2021 semester but is recommended for eventual integration into the final system.

### 4.3 Engineering Analysis and Experiment

Thorough sub-system experiment and analysis is inherently important to our proposed project as our final prototype is a fully integrated architecture that will allow us to complete our goal of autonomous trash removal. Reliable sub-system operation is critical to performing full system testing. Furthermore, as our project is mix of both software and hardware integration, coordinated attention must be placed within our sub-system testing to ensure the software libraries used function with our hardware. In this section, we detail how we will test and analyze these sub-systems as we are developing our platform.

**Detection Integration Testing and Analysis** The trash detection implemented by the Fall of 2020 team is critical in our proposed architecture. We will first move the previously trained model onto the Jetson TX2 and run the algorithm on the Trash-ICRA19 dataset [12] to ensure successful operation on our target on-board computer. This will allow us to experiment with how the bounding boxes are output by this system and evaluate for accuracy and performance. In the next step, we will integrate the new USB camera ensuring successfully image streaming capabilities to our system and evaluate performance. We will not be able to test integration with the object detection software until the camera is successfully mounted on the robot and ready to be deployed underwater. We will do intermediate experiments in this environment before the full system's integration in order to ensure that the detection model can detect trash objects underwater with our USB camera.

**Collision Avoidance and Navigation Testing and Analysis** Testing the collision avoidance and navigation capabilities of the robot can be done early on in the process as we will be using work completed in a previous semester. We will test our navigation and collision avoidance capabilities in a water environment before our full systems test. Furthermore, we will test our capability to transform and navigate coordinates in the local frame, using the global GPS frame.

**Trash Localization Testing and Analysis** Our first step in testing this sub-system will be to successfully install on our on-board computer and validate that we are able to localize and map using our USB camera as input. This testing can be done with just the computer and camera in lab, mapping the room and localizing the camera. In the next phase after the USB camera is installed with underwater capabilities, we will test underwater mapping and localization of the robot in a water environment with feature rich objects that ORB-SLAM can detect. Finally, we will run the same tests in less feature rich environment with only trash objects to see if the ORB-SLAM system is able to map their features.

## 4.4 Codes and Standards

There are several standards that apply to our design based on the hardware already implemented.

- **COLREGS:** is a set of navigation and collision rules that require detection of other vessels and yielding to less maneuverable traffic. The river robot should be designed to avoid other moving objects within the local environment [30].
- **SOLAS (Safetly of Life at Sea):** sets safety standards in the construction, equipment, and operation of merchant ships. The river robot should be able to detect marine animals, and avoid killing, harming, or capturing an animal [31].

- **Interim Guidelines for MASS Trials:** sets rules to ensure that the trials of autonomous ships are conducted in a safe and secure manner without interrupting the environment. The robot should not have any features that could interrupt the livelihood of the animals like unnatural sudden lights and/or sounds [32].
- **ISO/CD 24161:** defines internationally recognized terminology for waste collection and transportation management which will be necessary for the final goal of autonomous waste collection [33].
- **GPS Standard Positioning Service (SPS) Performance Standard:** defines the level of performance the U.S. Government makes available to civilians without special authorization. It ensures compatibility of GPS with systems operated by civilians [34].
- **FCC Radio Spectrum Allocation:** determines which portions of the electromagnetic spectrum can be used for different radio frequency applications within the U.S., and therefore our robot must fall within these guidelines for manual control and communication during operation as a maritime vehicle [35].
- **IEEE 802.11a/b/g/n/ac:** allows for the WiFi connection at 5 GHz standard and 2.4 GHz standard at wider channels (80 and 160 MHz). The robot would need a connection from the Jetson to the Kingfisher WiFi antenna [36].

Many of these standards are not of much concern to our design as our project mostly relies on software implementation using existing hardware which should already be compliant to these specifications. As regulations regarding operations of autonomous vessels are not well developed yet, they are also not much of a concern, especially in rivers and with a small craft where the chance for damage is minimal. Therefore, during this project, we must strive to develop a system which operates responsibly in the environment using our best judgment.



## 5 Schedule, Tasks, and Milestones

### 5.1 Gantt Chart

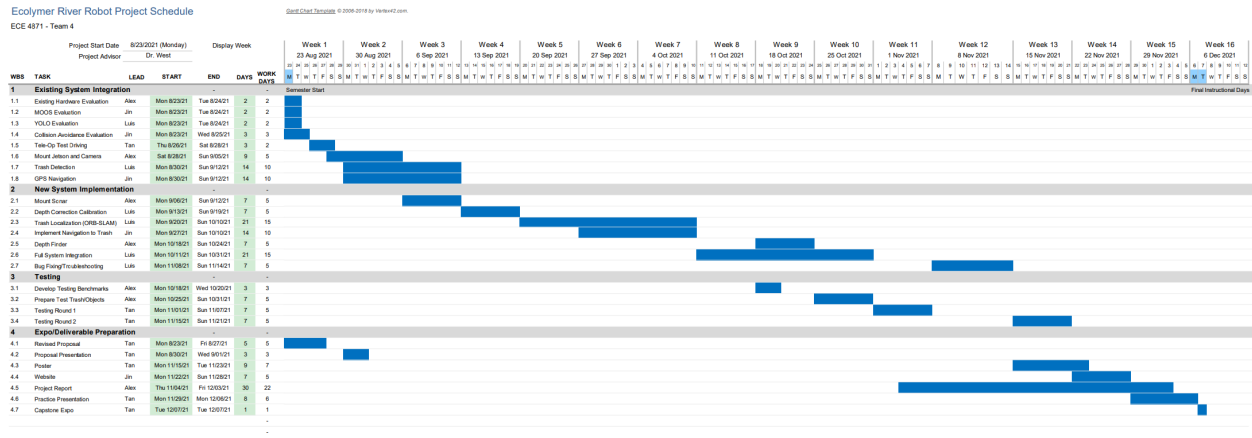


Figure 13: Gantt Chart for the Fall 2021 Semester. See Appendix A for expanded version.

### 5.2 PERT Analysis

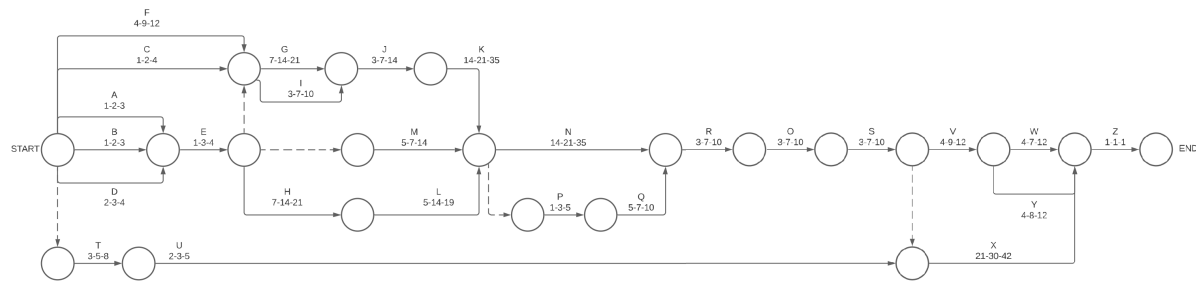


Figure 14: PERT Chart for the Fall 2021 Semester. See Appendix B for expanded version.

From our PERT chart, the critical path has been identified as CGJKNROS VWZ. These letters correspond to the tasks in our Gantt chart and are indicated in Figure 15. Based on our estimation of task durations, we have calculated the probability of our project being completed before the Capstone Expo to be 63.2% with an expected duration of 102.83 days. Due to this, we are going to have to be diligent in our work and very aware with our project timeline to stay on track for completion.

Ecolymer River Robot - Team 4

	Activity	Dependant On	Optimistic Time	Most Likely Time	Pessimistic Time	Expected Time	Std Dev
A	Existing Hardware Evaluation		1	2	3	2.00	0.33
B	MOOS Evaluation		1	2	3	2.00	0.33
C	YOLO Evaluation		1	2	4	2.17	0.50
D	Collision Avoidance Evaluation		2	3	4	3.00	0.33
E	Tele-Op Test Driving	A,B,D	1	3	4	2.83	0.50
F	Mount Jetson and Camera		4	9	12	8.67	1.33
G	Trash Detection	C,F	7	14	21	14.00	2.33
H	GPS Navigation	E	7	14	21	14.00	2.33
I	Mount Sonar	F	3	7	10	6.83	1.17
J	Depth Correction Calibration	G,I	3	7	14	7.50	1.83
K	Trash Localization (ORB-SLAM)	J	14	21	35	22.17	3.50
L	Implement Navigation to Trash	H	5	14	19	13.33	2.33
M	Depth Finder		5	7	14	7.83	1.50
N	Full System Integration	K,L,M	14	21	35	22.17	3.50
O	Bug Fixing/Troubleshooting	R	3	7	10	6.83	1.17
P	Develop Testing Benchmarks		1	3	5	3.00	0.67
Q	Prepare Test Trash/Objects	P	5	7	10	7.17	0.83
R	Testing Round 1	N,Q	3	7	10	6.83	1.17
S	Testing Round 2	O	3	7	10	6.83	1.17
T	Revised Proposal		3	5	8	5.17	0.83
U	Proposal Presentation	T	2	3	5	3.17	0.50
V	Poster	S	4	5	12	6.00	1.33
W	Website	V	4	7	12	7.33	1.33
X	Project Report	U,S	21	30	42	30.50	3.50
Y	Practice Presentation	V	4	8	12	8.00	1.33
Z	Capstone Expo	W,X,Y	1	1	1	1.00	0.00

**Critical Path:**

CGJKNROSVWZ

**Expected Duration:**

102.83

**Expected Standard Deviation:**

6.42

**Probability that the time to complete will be > 105:**

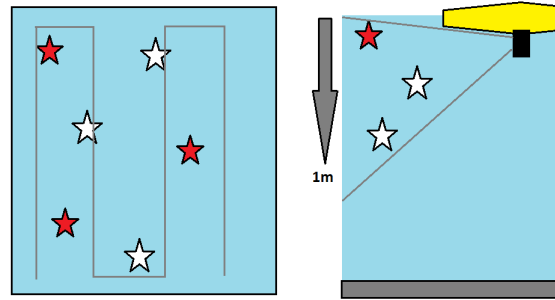
$$Z_s = (105 - 102.83) / 6.42 = .338$$

63.20%

**Figure 15:** Table detailing PERT Analysis for the Fall 2021 Semester.

## 6 Project Demonstration

We intend to demonstrate the vehicle through testing on a swimming pool with simulated trash being distributed throughout. An outdoor Olympic-size swimming pool will be the best option to prevent GPS interference from being indoor and provide plenty of operating space. We will provide the GPS coordinates for the path planning around the pool, irrespective of the location of the trash, and the robot will be challenged to correct identify and navigate over the trash when it detects it on its path. The simulated trash will be comprised of both clear and opaque plastic packaging and bottles that will be properly positioned to float within a meter of the surface of the water. We will not incorporate other objects that could potentially be under the surface of the water such as sticks or fish. We are also explicitly testing in a clean water environment where there will not be silt which would turn a river murky and reduce the vision capabilities of the camera. We will also place simulated obstacles in the path of the robot to test the collision avoidance. These will be comprised of overturned trash cans weighted-down with sandbags to simulate rocks or debris.



**Figure 16:** Expected conditions for initial testing of plastic detection with spacial distribution in the pool (left) and vertical distribution in the water (right)

We will record this performance for analysis and presentation at the Capstone Expo as we will be unable to provide an in-person demonstration there due to the size and set-up required.

## 7 Cost Analysis

As this project is primarily a proof-of-concept in testing the technologies required for the final goal of full autonomy, cost effectiveness is not a large concern with much of the components already available for us to use. Regardless, this section explores a cost analysis to see the feasibility of the direct commercialization of this prototype as a product at the end of our project. Additionally, we must still be aware of the impact our choices could have on the price of a final product derived from our conceptual prototype.

Two hourly rates are required for the development cost and manufacturing cost of the product. Using the typical electrical engineer starting salary of \$71,890/year [37] leads to an hourly cost  $\approx$  \$34 for development. Using the average engineering technician salary of \$53,566/year [38] leads to an hourly cost  $\approx$  \$26 for manufacturing.

The cost analysis was performed by identifying the cost associated with product research, development, and testing over the Fall 2021 semester, as shown in Table 5, which will then be distributed over an estimated number of units sold in five years. The part cost was identified in Table 6 through the available price of the required hardware components. It is notable that this is where the analysis is most inaccurate as multiple of the part choices here are dependant on hardware easily available to us for ease of development and would not be reflective of a true commercial product. Table 7 outlines the cost associated with individual manufacturing of the product where assembly is fairly simple but significant testing is required to ensure a high level of quality control. These results are combined in Table 8 to yield a unit selling price when considering overhead and adding an expected profit of 10%.

Task	Hours/Week/Engineer	# of Engineers	Hours Over 12 Weeks	Total Cost
Hardware	1	2	24	\$816
Software	3	3	108	\$3672
Deliverables	1	2	24	\$816
Meetings	2	4	96	\$3264
<b>Total Development Cost</b>				<b>\$8568</b>

**Table 5:** Development Cost Estimation.

Part Name	Quantity	Price	Source
Kingfisher M100	1	\$29,495	[1]
NVIDIA Jetson TX2	1	\$400	[39]
Kinect for Xbox One	1	\$40	[40]
Blue Robotics Camera	1	\$99	[13]
Blue Robotics Enclosure	1	\$112	[14]
Blue Robotics Echosounder	1	\$279	[25]
Arduino Uno Rev3	1	\$23	[28]
Tritech Micron Echosounder	1	\$1,995	[29]
Cables and connectors	—	Estimating \$200	—
<b>Total Unit Part Cost</b>			<b>\$32,643</b>

**Table 6:** Unit Part Cost Estimation.

Task	Hours	# of Technicians	Total Cost
Fabricate	4	2	\$208
Assemble	3	2	\$156
Testing	6	2	\$312
<b>Total Manufacturing Cost</b>			<b>\$676</b>

**Table 7:** Manufacturing Cost Estimation.

Development Cost	\$8568
Estimated Units Sold Over 5 Years	100
Development Cost Per Unit	\$86
Part Cost Per Unit	\$32,643
Manufacturing Cost Per Unit	\$676
<b>Total Cost Per Unit</b>	<b>\$33,405</b>
Expected Profit	20%
Overhead	10%
<b>Unit Selling Price</b>	<b>\$43,425</b>

**Table 8:** Suggested Selling Price Analysis.

## 8 Current Status

As demonstrated in the previous sections, we have completed the planning of this project and are ready to undertake full development at the onset of the Fall 2021 semester. We have been able to visit Dr. West's lab to see the Kingfisher M100 and additional hardware acquired by the previous teams. We have met with the current team to identify their progress and what tasks will need to be continued by us. We have performed a literature review to consider current technologies and other potential solutions available.

We intend to continue research and minor software development over the summer. We also have the potential to meet directly with the project sponsors at Ecolymer to inform them of our current plans for this project.

We will also need to purchase the outstanding parts required to complete this project and have outlined them in Table 9. This reflects the amount of funds requested in the introduction of this proposal. The remaining parts are available to us through Dr. West or from the previous teams working on this project.

### 8.1 Outstanding Parts Cost

Part Name	Quantity	Price	Source
Blue Robotics Camera	1	\$99	[13]
Blue Robotics Enclosure	1	\$112	[14]
Blue Robotics Echosounder	1	\$279	[25]
Arduino Uno Rev3	1	\$23	[28]
Cables and connectors	—	Estimating \$50	—
Testing Equipment	—	Estimating \$100	—
<b>Total Cost</b>			<b>\$663</b>

**Table 9:** Outstanding parts required for completion of the project during the Fall 2021 semester.

## 9 Leadership Roles

Leadership Roles				
Member	Luis Pimentel	Jin Bae	Tan Tonge	Alexander Chanthaphaeng
Roles	Software Co-lead Software Documentation	Software Co-lead Webmaster	Project Manager Expo Coordinator	Hardware Lead Team Documentation

**Table 10:** Leadership Roles for Fall 2021 Semester.

Leadership roles have been determined according to each team member's skill set to best leverage the capabilities of our team, as shown in Table 10.

- **Project Manger** will be responsible for organizing meetings, communication with outside contacts, and schedule management.
- **Software Co-leads** will be responsible for the primary development and final decisions relating to the software and firmware for the robot.
- **Hardware Lead** will be responsible for the implementation and fabrication needs relating to the hardware and sensors on the robot.
- **Software Documentation Coordinator** will be responsible for managing the Git Repository and technical documentation associated with the software algorithms.
- **Webmaster** will be primarily responsible for creating the team's website upon the completion of the project.
- **Expo Coordinator** will be primarily responsible for the presentation poster and deliverables associated with the Capstone Expo.
- **Team Documentation Coordinator** will be responsible for the deliverables associated with documentation deliverables throughout the semester.

## References

- [1] “Kingfisher m100 user manual,” Clearpath Robotics, Inc. [Online]. Available: <https://oceanai.mit.edu/svn/moos-ivp-kfish/trunk/docs/kfish-m100-manual.pdf>
- [2] “Sustainable development goal 14,” United Nations Department of Economic and Social Affairs. [Online]. Available: <https://sdgs.un.org/goals/goal14>
- [3] NOAA, “Why should we care about the ocean?” National Ocean Service. [Online]. Available: <https://oceanservice.noaa.gov/facts/why-care-about-ocean.html>
- [4] “River plastic emissions to the world’s oceans,” The Ocean Cleanup Technologies B.V. [Online]. Available: <https://theoceancleanup.com/sources>
- [5] H. Ritchie and M. Roser, “Plastic pollution,” *Our World in Data*, 2018, <https://ourworldindata.org/plastic-pollution>.
- [6] “The bubble barrier,” The Great Bubble Barrier. [Online]. Available: <https://thegreatbubblebarrier.com/technology/>
- [7] “Mr. trash wheel : A proven solution to ocean plastics,” Waterfront Partnership of Baltimore. [Online]. Available: <https://www.mrtrashwheel.com/>
- [8] “Alpla group,” ALPLA. [Online]. Available: <https://www.alpla.com/en>
- [9] M. Smith, D. C. Love, C. M. Rochman, and R. A. Neff, “Microplastics in seafood and the implications for human health,” *Current Environment Health Reports*, vol. 5, no. 3, pp. 375–386, 2018.
- [10] J. R. Platt and D. Kadaba, “The shocking number of florida manatees killed by boats last year,” The Revelator. [Online]. Available: <https://therevelator.org/2019-florida-manatees-killed/>
- [11] J. Redmon and A. Farhadi, “Yolo9000: better, faster, stronger,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 7263–7271.
- [12] M. S. Fulton, J. Hong, and J. Sattar, “Trash-icra19: A bounding box labeled dataset of underwater trash,” 2020, retrieved from the Data Repository for the University of Minnesota. [Online]. Available: <https://doi.org/10.13020/x0qn-y082>.
- [13] “Lowlight hd usb camera,” <https://bluerobotics.com/store/sensors-sonars-cameras/cameras/cam-usb-low-light-r1/>, Blue Robotics Inc., accessed: 2021-04-10.
- [14] “Watertight enclosure,” <https://bluerobotics.com/store/watertight-enclosures/2-series/wte-vp/>, Blue Robotics Inc., accessed: 2021-04-10.
- [15] B. Pitzer, “ros-drivers/usb\_cam,” [https://github.com/ros-drivers/usb\\_cam](https://github.com/ros-drivers/usb_cam), 2017.
- [16] J. Bowman and P. Mihelich, “ros-perception/image\_pipeline,” [https://github.com/ros-perception/image\\_pipeline](https://github.com/ros-perception/image_pipeline), 2020.
- [17] M. R. Benjamin, H. Schmidt, and J. J. Leonard. The moosivp open source marine autonomy project. [Online]. Available: <http://www.moos-ivp.org/>
- [18] R. Mur-Artal, J. M. M. Montiel, and J. D. Tardos, “Orb-slam: a versatile and accurate monocular slam system,” *IEEE transactions on robotics*, vol. 31, no. 5, pp. 1147–1163, 2015.
- [19] R. Mur-Artal and J. D. Tardós, “Orb-slam2: An open-source slam system for monocular, stereo, and rgb-d cameras,” *IEEE Transactions on Robotics*, vol. 33, no. 5, pp. 1255–1262, 2017.
- [20] F. Hidalgo, C. Kahlefeldt, and T. Bräunl, “Monocular orb-slam application in underwater scenarios,” in *2018 OCEANS - MTS/IEEE Kobe Techno-Oceans (OTO)*, 2018, pp. 1–4.

- [21] F. Hidalgo and T. Bräunl, "Evaluation of several feature detectors/extractors on underwater images towards vslam," *Sensors*, vol. 20, no. 15, p. 4343, 2020.
- [22] M. Ferrera, J. Moras, P. Trouvé-Peloux, and V. Creuze, "Real-time monocular visual odometry for turbid and dynamic underwater environments," *CoRR*, vol. abs/1806.05842, 2018. [Online]. Available: <http://arxiv.org/abs/1806.05842>
- [23] M. Roznere and A. Q. Li, "Underwater monocular image depth estimation using single-beam echosounder," 2020. [Online]. Available: <https://www.youtube.com/watch?v=JVTbxtM12yA>
- [24] M. Roznere and A. Q. Li, "Underwater monocular image depth estimation using single-beam echosounder," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2020, pp. 1785–1790.
- [25] "Ping sonar altimeter and echosounder," Blue Robotics Inc., accessed: 2021-04-10. [Online]. Available: <https://bluerobotics.com/store/sensors-sonars-cameras/sonar/ping-sonar-r2-rp/>
- [26] M. Roznere, "dartmouthrobotics/escalibr," <https://github.com/dartmouthrobotics/escalibr>, 2020.
- [27] "Ping echosounder sonar user manual," Blue Robotics Inc., accessed: 2021-04-10. [Online]. Available: <https://bluerobotics.com/learn/ping-sonar-technical-guide/>
- [28] "Arduino uno rev3," Arduino, 2021. [Online]. Available: <https://store.arduino.cc/usa/arduino-uno-rev3>
- [29] "Micron echosounder - ultra compact altimeter," Tritech International Limited, 2021. [Online]. Available: <https://www.tritech.co.uk/product/tritech-micron-echo-sounder-ultra-compact-altimeter>
- [30] "Convention on the international regulations for preventing collisions at sea," International Maritime Organization, 1972. [Online]. Available: <https://www.imo.org/en/About/Conventions/Pages/COLREG.aspx>
- [31] "International convention for the safety of life at sea," International Maritime Organization, 1974. [Online]. Available: [https://www.imo.org/en/About/Conventions/Pages/International-Convention-for-the-Safety-of-Life-at-Sea-\(SOLAS\)-1974.aspx](https://www.imo.org/en/About/Conventions/Pages/International-Convention-for-the-Safety-of-Life-at-Sea-(SOLAS)-1974.aspx)
- [32] R. Veal, "Interim guidelines for mass trials: Interim observations," 2019. [Online]. Available: <https://eprints.soton.ac.uk/435582/>
- [33] "Iso/cd 24161," International Organization of Standardization, 2021. [Online]. Available: [www.iso.org/standard/77957.html](http://www.iso.org/standard/77957.html)
- [34] "Global positioning system standard positioning service performance standard," Department of Defense, 2020. [Online]. Available: <https://www.gps.gov/policy/>
- [35] "Radio spectrum allocation," Federal Communications Commission, 2021. [Online]. Available: [www.fcc.gov/engineering-technology/policy-and-rules-division/general/radio-spectrum-allocation](http://www.fcc.gov/engineering-technology/policy-and-rules-division/general/radio-spectrum-allocation)
- [36] "What are ieee 802.11 standards? : 802.11a/b/g/n/ac/ax," IEEE, 2020. [Online]. Available: <https://www.signalboosters.com/blog/ieee-802.11-standards-explained-802.11abgnacax/>
- [37] "Entry level electrical engineer salaries in united states," Glassdoor, Inc., 2021. [Online]. Available: <https://www.glassdoor.com/Salaries/entry-level-electrical-engineer-salary-SRCH.KO0,31.htm>
- [38] "Engineering technician salaries in united states," Glassdoor, Inc., 2021. [Online]. Available: <https://www.glassdoor.com/Salaries/us-engineering-technician-salary-SRCH.IL0,2.IN1.KO3,25.htm>
- [39] "Nvidia jetson tx2 developer kit," Seeed Technology Co.,Ltd., 2021. [Online]. Available: <https://www.seeedstudio.com/NVIDIA-Jetson-TX2-Developer-Kit-p-4413.html>
- [40] "Kinect xbox one," GameStop Corp., 2021. [Online]. Available: <https://www.gamestop.com/video-games/xbox-one/accessories/controllers/products/kinect-xbox-one/10115985.html>



## A Expanded Gantt Chart

### Ecolymer River Robot Project Schedule

Gantt Chart Template © 2006-2018 by Vertex42.com.

ECE 4871 - Team 4

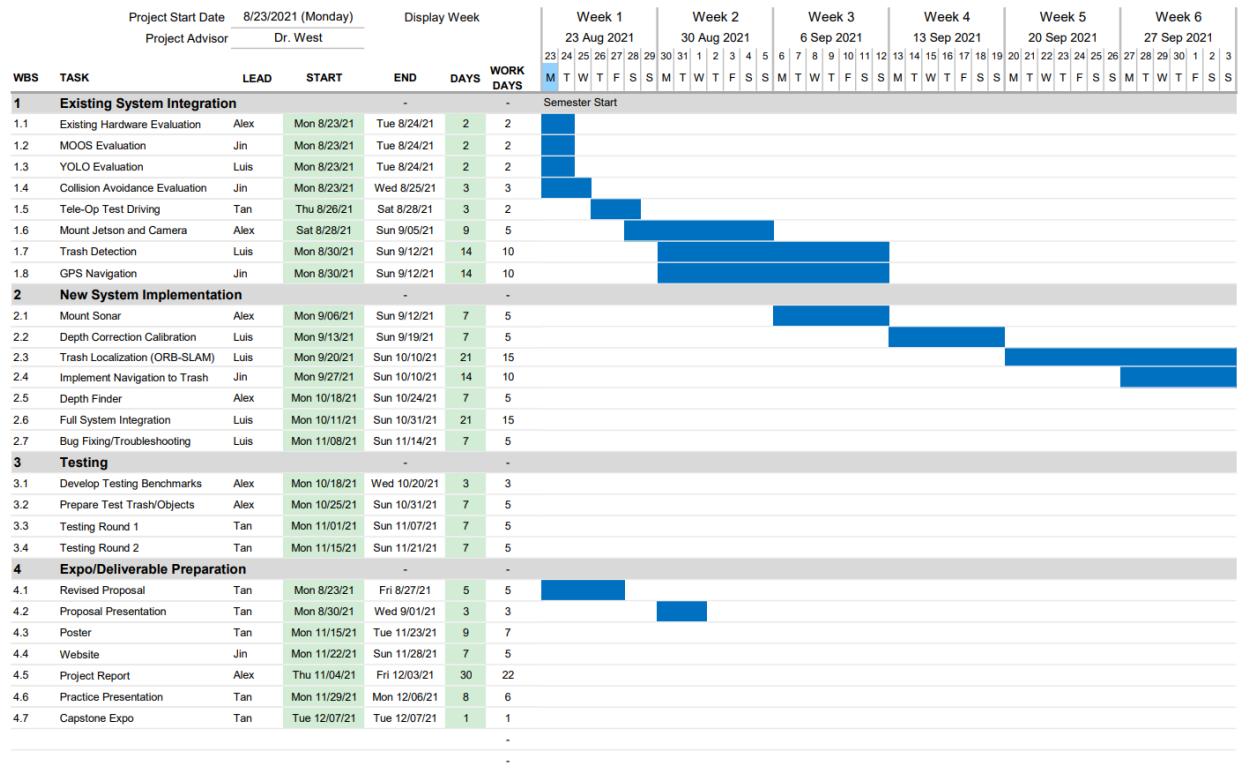


Figure 17: GANTT 1/3

## Ecolymer River Robot Project Schedule

ECE 4871 - Team 4

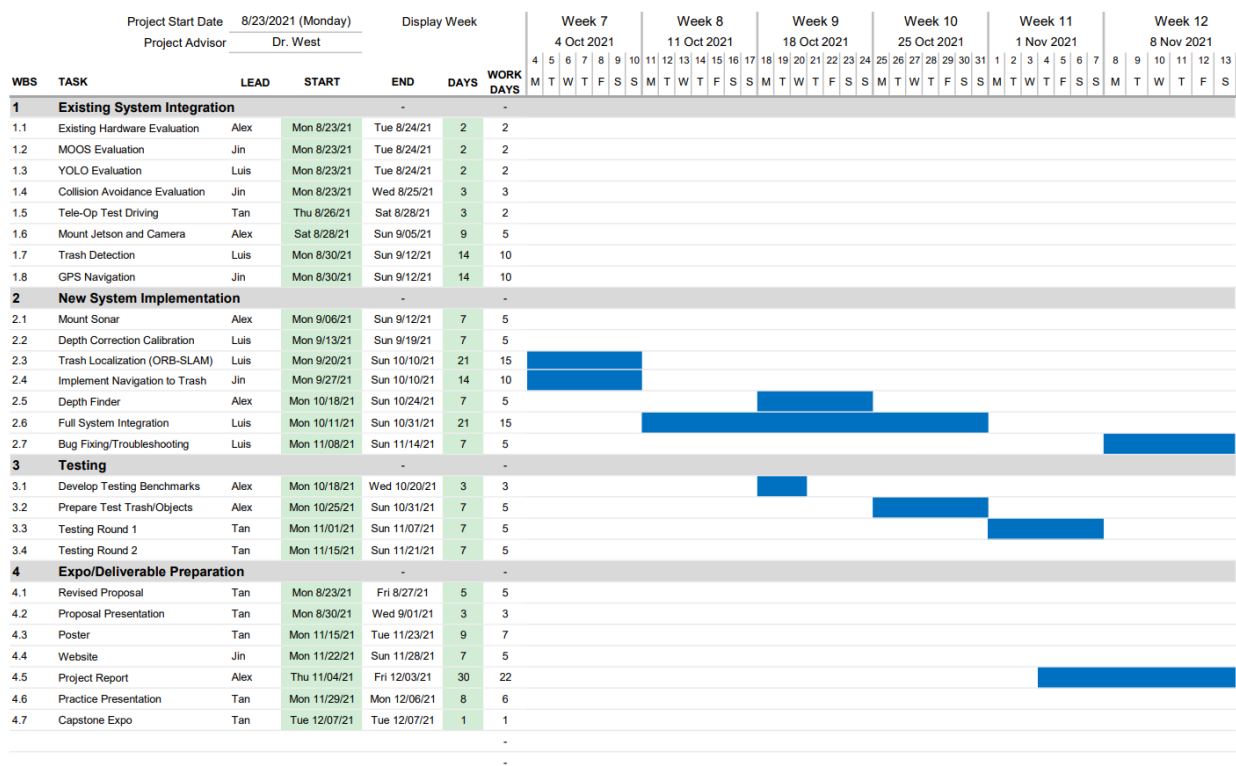


Figure 18: GANTT 2/3

ECE 4871 - Team 4

**Figure 19:** GANTT 3/3

```
graph LR; START((START)) --> A((A 1-2-3)); START --> B((B 1-2-3)); START --> C((C 1-2-4)); START --> D((D 2-3-4)); START --> E((E 1-3-4)); START --> F((F 4-9-12)); START --> T((T 3-5-8)); A --> B; B --> E; C --> G((G 7-14-21)); D --> E; E --> G; E --> H((H 7-14-21)); E -.-> I((I 3-7-10)); F --> G; F --> J((J 3-7-14)); G --> I; I --> J; H --> L((L 5-14-19)); J --> K((K 14-21-35)); K --> M((M 5-7-14)); K --> N((N 14-21-35)); L --> M; M --> N; N --> R((R 3-7-10)); P((P 1-3-5)) -.-> M; P --> Q((Q 5-7-10)); Q --> R; R --> FINISH((FINISH)); T --> U((U 2-3-5)); U --> FINISH;
```

```

graph LR
    R((R  
3-7-10)) --> O((O  
3-7-10))
    O --> S((S  
3-7-10))
    S -.-> X((X  
21-30-42))
    X --> W((W  
4-7-12))
    S --> V((V  
4-9-12))
    V --> W
    V -- Y 4-8-12 --> W
    W --> Z((Z  
1-1-1))
    Z --> END((END))
  
```

35 of 35