

Laser Quadrat and Photogrammetry Based Autonomous Coral Reef Mapping Ocean Robot

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Abstract

Coral reef ecosystems are some of the diverse and valuable ecosystems on earth. They support more species per unit area than any other marine environment and are essential to the sustenance of life in our oceans. However, due to climate change, only under 46% of the worlds coral were considered healthy as of 2008. One of the biggest challenges with regard to coral conservation is that reef mapping is currently carried out manually, with a group a divers manually moving and placing a large PVC quadrat for every unit area of the reef and then photographing and analyzing each unit separately. Hence, there is a pressing need to improve the methodology of imaging, stitching and analyzing coral reef maps in order to make it feasible to protect them and sustain life in our oceans.

To improve the current methodology, a reef-mapping surface drone robot which photographs, stitches and analyzes the reef autonomously was built. This robot updates the physical quadrat which is used today, to a projected laser quadrat, which eliminates the need to dive to the bottom of the sea and allows relative pose estimation. The robot then captures and processes the images and using 3D reconstruction and computer vision algorithms is able to map and classify the coral autonomously.

Introduction

The role and importance of coral reefs in the supporting ecosystem of life in our oceans is often understated. Coral reefs are the nurseries of the oceans and support more species per unit area than any other marine environment, including about 4,000 species of fish, 800 species of hard corals and hundreds of other species as well as provide goods and services worth USD375 billion each year [1]. Fishing and Tourism, which very often make up the core economic industry for many countries has direct dependencies to the health of the coral reefs in that area. Thus, it is absolutely essential for us to ensure the continued health of these reefs in the interest of protecting the livelihood of millions of coastal communities worldwide.

As global temperatures rise due to climate change, our coral reefs are deteriorating quickly. The organisms that are responsible for creating and maintaining coral reefs are highly sensitive to these temperature changes and thus, as global temperatures rise, coral reefs start to lose their color in a process called coral bleaching until they eventually die. Only about 46 percent of the worlds coral were considered healthy in 2008 and this percentage has dropped further recently. The years 2014-2017 saw the worlds largest coral bleaching event yet [2].

As we face this global ecological crisis, there exists a pressing need to map the worlds coral reefs in order to fully understand the extent of damage right now. Mapping also helps coral conser-

vationists plan how to best approach nurturing a particular reef back to health. A year-on-year mapping of a reef allows to track bleaching over the years with successive maps and gives us reef health benchmarks from the past.

A major challenges with regard to coral conservation is that reef mapping is currently carried out manually, with a group a divers manually moving and placing a large PVC quadrat for every unit area of the reef and then photographing and analyzing each unit separately. This process is time-consuming, dangerous for the divers as well as expensive resulting in an unfavourable coral monitoring process. Further, at a global scale it would be unfeasible to map coral reefs this way. Hence, there is a pressing need to improve the methodology of imaging, stitching and analyzing coral reef maps in order to make it feasible to protect them and sustain life in our oceans.

To improve the current methodology, a reef-mapping surface drone robot which photographs, stitches and analyzes the reef autonomously was built. This robot updates the physical quadrat which is used today, to a projected laser quadrat - which eliminates the need to dive to the bottom of the sea and allows relative pose estimation. To streamline the mapping process, the robot captures images from the water surface using an on-board camera. It then color corrects the captured images to make them suitable for analysis following which it stitches successive images into image chunks. The robot then uses the laser quadrat and image data to generate a 3 dimensional reconstruction of the 2 dimensional reef floor image chunks and computer vision algorithms are able to map and classify the coral autonomously. Successive maps can then be compared across multiple pixels to understand the extent of bleaching of the reef at different points and different dates. This this technology could prove to be a leap forward in the world of ocean based instrumentation and has the potential to create far-reaching impact to reefs around the world.

Platform and Subsystems Requirements and Motivations

A thorough analysis of the problem revealed to us the key issues of the challenge that required to be tackled. Ease of image capture, speed of mapping, scalability and cost of the proposed solution were the core metrics around which the solution would have to be designed. With regard to accuracy, some loss in resolution compared to divers was found to be acceptable. The platform would also have to be friendly to the non-technical members of coastal communities since they are the largest stakeholders in the problem space. Thus, our goal was to design and build a platform that can image and map coral reefs 10X Faster, 10X more Accurate an 10X Cheaper than manual diver coral survey. A number of imaging techniques and physical platforms were studied to see

which one makes an ideal for tackling this problem. Eventually, the proposal was to build an autonomous surface borne reef mapping boat. The trade-off here would be a lower resolution compared to an underwater system and thus greater challenges in processing the obtained images. Further, maintaining the camera's position during image capture can be challenging on the choppy water surface. However, our motivation for choosing this sort of platform was that this method delivers a very quick, repeatable, cost-effective solution to the problem and provides the optimum trade-off in terms of the problem requirements for replacing human divers.

Resultant Platform

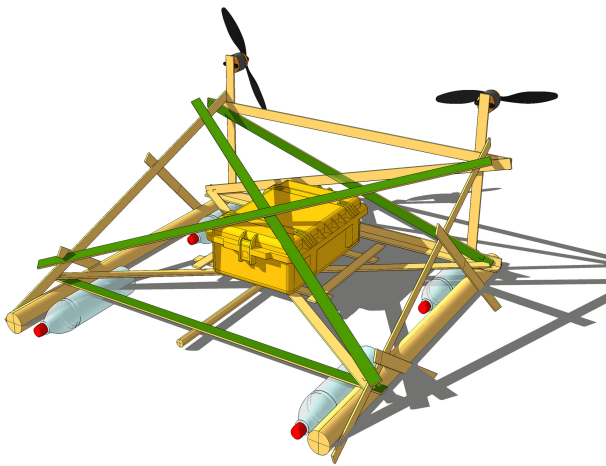


Figure 1. Resultant Platform Concept



Figure 2. Resultant Platform Implemented

Overview

After studying the challenge and motivations an unmanned boat with a laser quadrat and camera was developed to photograph coastal underwater corals. The idea was born from aerial drone aerial mapping where flying drones create 3D maps of landscapes

below using their height to get an appropriate reference frame, used now for coastal coral reefs mapping with georeference. The new custom designed Ocean Drone is made for efficiency and durability in the sea. A combination of lightweight and strong acrylic, flexible bamboo and vulcanized rubber was used to attain a lightweight (3 kg) and durable frame. The materials combined with smart design allowed it cruise steadily even through rough seas with a maximum speed of 9.7 knots. RC Water Jets (NQD 757-6024 RC Boat Turbojet) or brush-less motor propellers both can achieve this speed.

With regard to imaging, the robot calculates coral bleaching/live coral cover using color correction and image processing techniques and returns the same as a percentage. The on board laser quadrat provides us with a depth reference for reef analysis. Finally, using sequential pairs of images, coupled with GPS data and laser quadrat information, the robot autonomously delivers a 3D map of reef sections. Thus, the robot streamlines the entire process of reef mapping by updating manual to autonomous, physical quadrat to laser quadrat, manual classification with an algorithm.

Key Subsystems

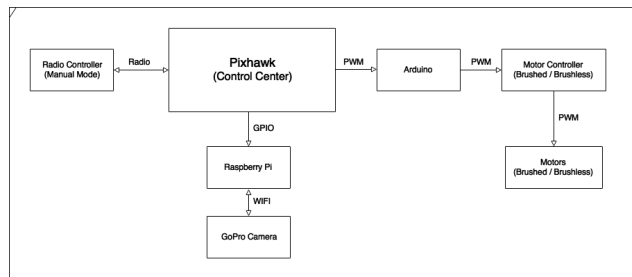


Figure 3. Key Subsystems

The electronics system on board the sailing robot has three main purposes controlling the direction of the robot, planning the mission for the robot and capturing images of the coral reef along its journey. Our aim was to develop a system which is low cost and easy to develop and document, so that it is easier to understand and contribute towards the technology of the system. For the purposes of this paper, we will not be discussing the motor control systems and autonomous navigation sections of the electronics in detail.

Our system is built on a commercially available open-source drone control system Pixhawk and uses a GoPro and Raspberry Pi to make the imaging section run smoothly. It contains the required digital sub-systems for both manual and auto-pilot control of our robot- such as GPS, IMU and Radio Control with a well-documented API. It has a high expandability since it has IO channels, including Serial Ports, I2C and GPIO. Additionally, In order to control geotagging and capture photos in real time, a Raspberry Pi is used to trigger a GoPro Camera. The Raspberry Pi itself receives a signal from the Pixhawk when a picture needs to be taken. The Raspberry Pi also acts as a metadata logger for the entire system, maintaining a list of the timestamped title of the images captured in a single run.

Imaging Setup

The imaging system primarily consists of three components. Mainly, a Raspberry Pi, a GoPro camera and a 3 axis stabilization gimbal. The gimbal was attached upside-down along the vertical axis of the center of the robot. The GoPro camera was attached to this gimbal with a wire extending out for the external battery. The gimbal provides camera stability when the robot encounters waves. The Raspberry Pi was housed in a separate section and communicated with the GoPro over Wi-Fi. HTTP was the protocol of choice since the GoPro supports HTTP REST requests which can be triggered through the Linux command line provided the appropriate packages. The Raspberry Pi received the GPS location from the Pixhawk flight controller and triggers the GoPro camera as the GPS location changes by a certain threshold. It then logs all the time-stamp, GPS location and photograph from the GoPro and runs the color correction and image processing algorithms on the stored images. GoPro was chosen as our camera for several reasons. Not only does it provide a high image quality, but it also provides a software API (with unofficial Raspberry Pi support) for all the settings and control. It acts as a Wi-Fi network server so that the Raspberry Pi client can trigger it.

Methodology and Observations

To tackle this challenge from an imaging perspective the process of photographing and mapping was divided into four stages:

Color Correction

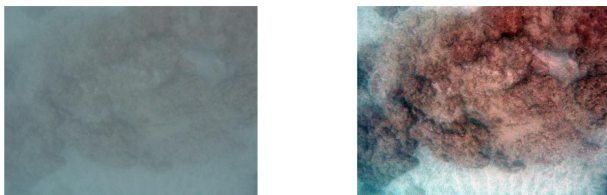


Figure 4. Before and After Color Correction

The very step of the process is to prepare the actual images for further processing. Due to turbidity, brightness, angle of sunlight and other environmental factors the image quality can vary quite significantly and needs to be corrected to a standard[3]. There are many techniques to achieve this. One is to place a color calibration chart on the image frame to act as a reference for the camera. Alternatively, since we have a laser quadrat that is sending out a fixed wavelength of light, we can use the laser color to calibrate our image. We can also use sensor data (angle of sunlight, brightness etc) and further improve our calibration in real-time. However, in our case we decided to manually set the calibration parameters such as brightness, contrast and the color curves at the beginning of each run. The manually set parameters are then replicated for all the images taken over the next run.

Image Stitching

As the robot moves ahead, images are taken consecutively. This ensures high overlap between the images. Consecutive images are stitched to create images of reef chunks. When the overlap is over 75% (which is most of the time) our algorithm is highly successful in stitching the images. The basic process can be sum-

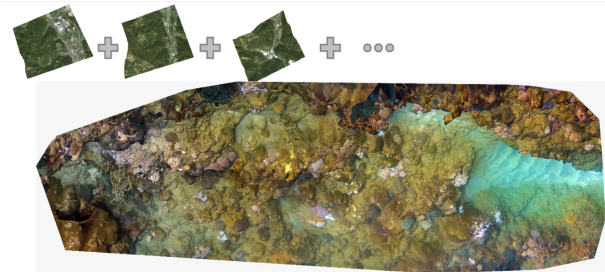


Figure 5. Image Stitching

marized as below:

- 1) Detect keypoints and extract local invariant descriptors (SIFT) from the two input images[4].
- 2) Match the descriptors between the two images.
- 3) Use the RANSAC algorithm to estimate a homography matrix using our matched feature vectors.
- 4) Apply a warping transformation using the homography matrix.

Image Processing

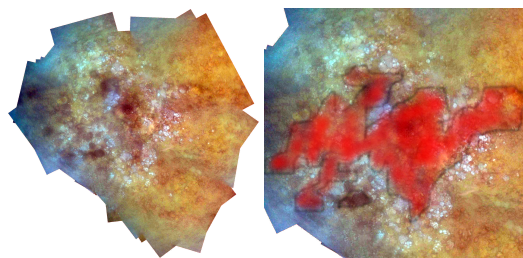


Figure 6. Stitched Chunk vs Live Coral Cover

Now that we have stitched image chunks, our goal is to obtain the live coral cover from these images. This is a straightforward thresholding process. Coral bleaching is determined based on the color of the coral being analyzed.[5] On this basis, bleaching "bands" are estimated according to the color of the coral. Here, we use thresholding on the color corrected images to determine which bleaching band a particular coral is in. Using this, we can generate a percentage live coral cover for the reef section in the stitched image chunk.

Laser quadrat

To provide a more complete view of the coral reef, the team decided to take multiple images along a predetermined line and stitch them together to create a map with realistic top-down view of the corals. In order to measure the real size of the corals, there needs to be a reference frame in the picture. The robot uses perpendicular laser beams to create this reference frame.

Line Based Quadrat

The laser lines form a square, which is fixed-size regardless of the water depth. This square will be captured in the image, and the task is to extract the pixels inside this square and save them as a new image, which will then be used for map generation. The final map will have corals of consistent relative size and the distance can be measured with good accuracy. To accomplish this

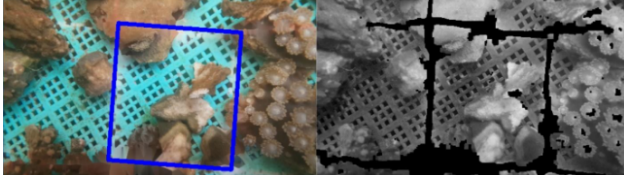


Figure 7. Line Based Quadrat

task, we use OpenCV for image processing. Since the laser is red in color, first, we perform red color detection on all intensity levels to obtain a binary map. Next, we perform a morphological closing operation on this binary map to connect nearby regions of red color. Then, we need to find contours and filter them to identify the one that contain the desired square. In detail, we find contours whose size is within a certain range (500 1000 pixels). The range is determined empirically depending on the resolution of the input images. Also, the desired contour should have red edges and the center of other colors; the original area should not differ too much the area of the minAreaRectangle. After a good contour is identified, we construct a minAreaRectangle, extract the pixels enclosed in the rectangle and save them as an image. If there is not a good contour, the program returns fail.

Point Based Quadrat

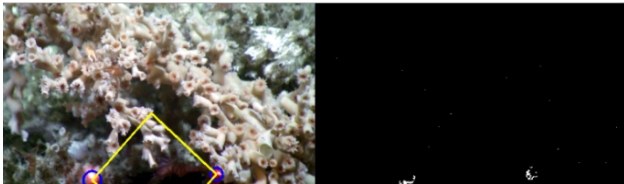


Figure 8. Point Based Quadrat

To enhance the concentration of the laser beams, we use 2 laser points to mark the top-left and bottom-right vertices of the square. From these two points, we can construct a fixed-size square to extract the pixels from[6]. Our algorithm implements the following steps:

+ Perform red color detection with HSV value ranging from (176, 100, 100) to (179, 255, 255). Since it is harder to filter point contours compared to quadrat contours, the color range need to be more specific. Again, this range is determined empirically. The result of this step is a binary mask showing where the red points are.

+ Run contour detection algorithm on the binary mask and

$$\begin{cases} (x-ox)dx+(y-oy)dy=0 \\ (x-ox)^2+(y-oy)^2=dx^2+dy^2 \end{cases}$$

choose the contours whose areas are larger than 100 pixels and smaller than 1000 pixels. Next, draw a minimum enclosing circle and obtain the coordinate of the contour center. If there are less than or more than 2 contours, iteratively increase or decrease the color range and size filter range until exactly 2 contours are found. If a 2-contour result is not achievable, return fail.

+ Construct a square from the diagonal formed by the 2 laser points: Find the center of the square (ox, oy), the vector of the

diagonal (dx, dy) and solve the following equation to find the coordinates of the other 2 vertices (x, y).

+ Extract the pixels enclosed by the square: Find the rotation angle of the square; obtain the rotation matrix for a angle; rotate the image so that the edges of the square are parallel/perpendicular to the axes; use the rotation matrix to identify the new center of the square; finally, extracts the pixels from the square and save them as a separate image.

3D Reconstruction

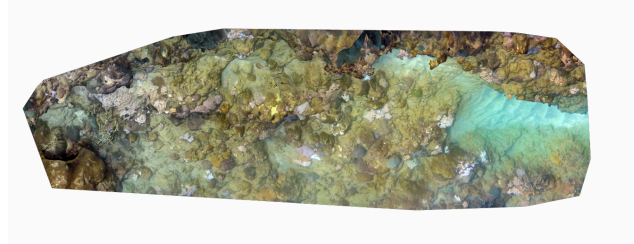


Figure 9. 2D image before reconstruction

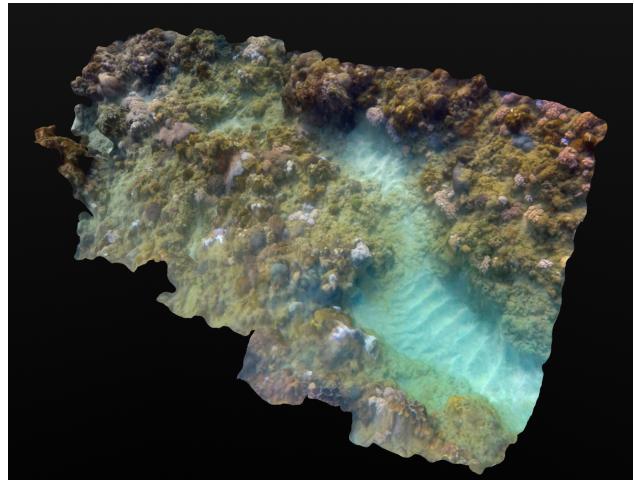


Figure 10. 3D Reconstruction

The last and final step of the process is to generate the 3D map from the 2D image. For this, we first calculate the depth from the laser quadrat to get a reference frame. To do this, we see the position of the dots in the image. The width of the dots gives us an idea of how deep the reef section we are looking at is. From, this we can make a good estimation of the pose of the robot and the scene. We now take a set of consecutive images taken by the robot. We calculate the distance between the geo-locations of these images from the GPS logs. What we now have is effectively a set of stereo images with a fixed distance between them. We can now match features between these images and use triangulation, coupled with data from the laser quadrat to improve accuracy. Using this, we can generate a matrix to estimate the 3D position of the image pixels. Now that we have this, we generate a 3D projection of our 2D image chunk[7].

Errors

Image Correction Errors

Some possible issues with the analysis may lie in the use of color correcting algorithm and manual parameter setting which may affect the visibility of different areas of dead and living corals; however, all corals were color corrected using the same software, allowing for no discrepancies between differing images. However, eventually the goal is to develop an automatic color correction system using either a color calibration chart, the laser quadrat beam or sensor data to set the calibration parameters. Issues with color correction can lead to errors of up to 10% in our live coral cover estimation algorithm.

3D Reconstruction Errors

Additional errors may arise from issues regard depth, such as resolution. In some image chunks, it was impossible to determine if the white corallite structures were images of still healthy coral bodies or empty corallite structure leftover from dead corals since the image was taken with the coral's being quite deep. Further, after about 8m in depth, the laser becomes very faint in our images due to which an accurate 3D reconstruction becomes near impossible. With greater depth, the image quality is highly sensitive to environmental factors and is prone to resulting in poor responses and lower accuracy from our stitching and processing algorithms.

Conclusion

Mapping Method vs Order of Magnitude of parameter

Method	Time	Cost(USD)	Resolution
Satellite	1 second	1,000,000	1px= 10m
Plane/UAV	1 minute	100,000	1px= 1m
Ocean Drone	1 hour	1,000	1px= $10^{-3}m$
Driver	1 day	100	1px= $10^{-6}m$

Maps generated with manual photography still showcase better resolution to the ocean drone by the order of 103 but take very long to generate. The ocean drone does seem to provide an advantageous balance between cost, time and image quality with regard to mapping reefs. The laser quadrat image reconstruction technique and automated bleaching calculation and mapping is highly advantageous to coral scientists. Overall the robot reduces mapping time by x5, analysis time by x6 and cost by x2 with the trade off being a resolution loss. In the future, further improvements are to be carried out to the image capture systems to improve their resolution and make the autonomously generated map close to a manually developed one. Image correction needs to be standardized depending on the environmental conditions and light availability. A relationship between the image parameters and the actual environmental conditions needs to be established to allow for better accuracy in image processing output. Overall, the technology is a significant jump forward in evaluating coral health and it is critical that it be developed further if we are to

effectively assess the health of oceans and mitigate the effects of climate change.

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Author Biography

Sidhant Gupta is a current undergraduate student at the University of Hong Kong studying computer engineering. His research interests lie in the application of computer vision and electronic imaging in creating social impact.

Thanh Tung Bui received his BEng in Computer Science from the University of Hong Kong (2018). Since then he has been working with computer vision and virtual reality systems with Japanese technology company Rakuten.

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Edmund Lam received the PhD degree in electrical engineering from Stanford University in 2000. He is now an associate professor in electrical and electronic engineering and a co-director of the computer engineering program at the University of Hong Kong. He is also the founding director of its Imaging Systems Laboratory. He currently chairs the SPIE conference on Image Processing: Machine Vision Applications, part of the Electronic Imaging symposium. He is a senior member of SPIE.

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