Reconfigurable Robots for Scaling Reef Restoration

Serena Mou, Dorian Tsai and Matthew Dunbabin
Queensland Centre for Robotics
Queensland University of Technology
Brisbane, Australia
serena.mou@hdr.qut.edu.au, {dy.tsai, m.dunbabin}@qut.edu.au

Abstract—Coral reefs are under increasing threat from the impacts of climate change. Whilst current restoration approaches are effective, they require significant human involvement and equipment, and have limited deployment scale. Harvesting wild coral spawn from mass spawning events, rearing them to the larval stage and releasing the larvae onto degraded reefs is an emerging solution for reef restoration known as coral reseeding. This paper presents a reconfigurable autonomous surface vehicle system that can eliminate risky diving, cover greater areas with coral larvae, has a sensory suite for additional data measurement, and requires minimal non-technical expert training. A key feature is an on-board real-time benthic substrate classification model that predicts when to release larvae to increase settlement rate and ultimately, survivability. The presented robot design is reconfigurable, light weight, scalable, and easy to transport. Results from restoration deployments at Lizard Island demonstrate improved coral larvae release onto appropriate coral substrate, while also achieving 21.8 times more area coverage compared to manual methods.

Index Terms—marine robotics, environmental robotics, deep learning for visual perception, coral reef restoration

I. INTRODUCTION

Coral reefs are under extreme pressure from impacts linked to climate change [1]–[4]. Coral reseeding is a restoration technique pioneered by Harrison et al., where “slicks” of wild coral sperm and eggs released during mass spawning events are harvested from the ocean surface, fertilised, reared until the larval stage, and the larvae released onto target reefs [5]. This allows for the placement of the coral larvae onto appropriate substrates that greatly increase their chance of survival, and has been shown to successfully restore populations of coral [5], [6]. However, most reef restoration projects have been relatively small in spatial scale with the median size of restored reef of approximately 100 m$^2$ [7]. Additionally, current deployments involve manually intensive processes with significant diver and vessel costs [8]. To perform restoration deployments at the scale of the Great Barrier Reef [9], automation is essential [7], [8].

In this paper, we present FloatyBoat, shown in Fig. 1, a novel Autonomous Surface Vehicle (ASV) which was developed to automatically and precisely deploy coral larvae across entire reefs. Our key contributions are the design of a reconfigurable ASV platform with an on-board automatic vision-based substrate classification algorithm that operates in real-time to control the larvae deployment pumps; all managed and deployed via an app. This allows for scaled up reef restoration that does not require trained divers or technical experts in the field. We demonstrated the utility of these contributions through restoration deployments at reefs off Lizard Island, the Great Barrier Reef, and in the Philippines.

II. RELATED WORK OF MARINE ROBOTS

Existing underwater robots and surface vehicles are often highly-specialised for their application [10]–[13]. As a result of this specialisation, their usefulness for other tasks can be limited. Given the high costs of running a robot, a narrow usage case limits the usefulness and applicability of the robot for intensive tasks such as reef restoration. Reconfigurable robots are one approach to alleviate this issue.

Previously proposed for reef restoration, the Rangerbot Autonomous Underwater Vehicle (AUV) was developed for modularity and has been deployed for deep and precise coral larvae placement [8]. Whilst suitable for deeper water deployments, the Rangerbot has a smaller larvae carrying capacity which ultimately lowers coverage. It is also unsuitable for harvesting coral slicks. A more suitably designed surface vehicle for coral reseeding offers a greater payload, endurance and multi-function opportunities.

III. FLOATYBOAT: A RECONFIGURABLE AUTONOMOUS SURFACE VEHICLE

A. Design Considerations

FloatyBoat was designed as a multi-purpose conservation tool to complement the RangerBot AUV for shallow reef restoration around the world [8]. The key system components for coral slick collection and larvae deployment are shown in

Fig. 1: A sample fleet of modular FloatyBoats configured for capturing coral spawn (left), monitoring and 3D mapping reefs (middle), and deploying coral larvae (right).
FloatyBoat configured for larvae collection, driving backwards to scoop up coral spawn which floats at the surface (left), then scooped out into boats for collection (right).

FloatyBoat ASV uses two thrusters for differential control, giving it an endurance of two hours at 0.75 m/s on a single battery. The sensing payload for reef restoration is typically configured with a camera and a small onboard computer with a GPU (NVIDIA Jetson Nano) for image processing, and GPS, compass and depth sounder for remote control or autonomous navigation. The controller is capable of following a path with less than 0.5 m cross track error, and can coordinate with other ASVs in swath formations such as a line and V-patterns.

The relatively low-cost of FloatyBoat stems from the use of high-performance micro-controllers and the ability to quickly reconfigure the robot without any structural changes. The U-shape of the boat was a deliberate decision to allow the additions of payload systems such as spawn collection nets (Section III-B), larvae bladders (Section III-C), and retractable sensors (e.g. high-resolution cameras and sonars) for mapping and monitoring (Section III-D). The ASV can be deflated and packed for transport, then re-inflated with a hand pump upon arrival.

B. Coral Larvae Collection

To collect coral spawn slicks, the FloatyBoat is configured with a fine mesh net as shown in Fig. 2. In this mode, the controller is reversed to drive the ASV in the direction of the net opening, thus skimming the floating spawn from the water’s surface into the net.

C. Coral Larvae Dispersal

For coral larvae dispersal, the FloatyBoat is configured with a 100L larval bladder, and a multi-pump with a multi-delivery hose system. Together, the system allows for larvae deployment rates of up to approximately 10,000 larvae per m² across the reef. The dispersal configuration is shown in Fig. 3.

1) Substrate Classification: Larvae dispersal is regulated by the coral substrate classification camera system. Coral larvae are more likely to settle near other hard corals and on solid rock; they are unlikely to settle on or near soft corals, sandy bottoms, algae or loose rubble substrate. Thus, a system that can decide whether the substrate below the ASV is suitable for restoration can improve settlement success and prevent wastage of precious larvae.

To determine the suitability of substrates, image classification was selected over pixel-wise segmentation – primarily because localisation within the image was unnecessary and it allows for computationally cheaper models. Convolutional Neural Networks (CNNs) are currently the state-of-the-art for image classification. MobileNetV3 is a CNN designed for mobile phone CPUs, and was thus ideal for lightweight mobile robotic platforms, such as the FloatyBoat. We adapted MobileNetV3 into a binary image classifier to predict whether or not a given image was either suitable or unsuitable substrate for coral recruitment.

We obtained over 2,254 1920x1200 pix images from both Heron Island and Lizard Island to train and test our classifier. Images were labelled manually using expertise from marine scientists. To enable generalisation and robustness, data augmentations were applied during training. The images were randomly flipped and rotated, and small shifts to the colour-space were randomly applied. Table I summarises the performance of the classifier. The images from each location were randomly split into balanced training, validation and test sets. The accuracy is shown along with the F1-score for each class. The F1-score incorporates the precision and recall of each class to provide a single more detailed metric for evaluation. Some typical examples of suitable (green) and unsuitable (red) substrates are shown in Fig. 4. The highest performing model across both test sets was trained on both the Lizard and Heron data (Combined); however it should be noted that this was only by a small margin.
D. Coral Monitoring

The coral monitoring configuration for FloatyBoat uses a retractable boom camera placed over the hull’s U-section as in Fig. 5 While the camera from the dispersal system was sufficient for navigation, control and substrate classification, the boom camera was designed to minimise self-shadow and the images were collected at a much higher resolution for 3D reconstruction. The ASV automatically traverses an area in a coverage pattern at a pre-selected track width that provides sufficient overlap for photogrammetry.

E. FloatyBoat Operation

An essential aspect of using robots for large-scale deployments is that non-technical experts must be able to operate the systems. The ASV is tasked using an app with a graphical user interface (GUI) that focuses on high-level control, such as waypoint planning and payload configuration-dependent operations. A “fuel gauge”-like feedback was implemented to show an estimate of the larvae remaining in the bladder, and an overlay of dots across the trajectory was used to summarise suitable substrate on the GUI. Up to seven ASVs can currently be controlled using the app. Live images from the ASV can be displayed, although bandwidth limitations during deployments currently prevent doing so in the field.

IV. Field Results

FloatyBoats were deployed across several reefs for coral restoration. On the Great Barrier Reef, two ASVs were used at Lizard Island (Loomis and Watson Reefs) in 2021, Heron Island Reef in 2020, as well as in the severely degraded reefs in the Philippines in 2021 and 2022. At each deployment, the collection, dispersal, mapping and training processes were refined.

A. Coral Larvae Collection

Larvae collection was successfully and efficiently accomplished using two FloatyBoats. With only 8 x 100 m transects, over 170L of larvae were collected during the 2021 Lizard Island spawning. The total collection time was ~50 min with only two human operators. This time included re-positioning the ASVs three times due to being blown off station by wind. While no direct comparison to manually collecting coral spawn was made, under sparse slick conditions the ASVs provide much farther reach and maneuverability compared to a single crewed boat with many deck hands and buckets.

B. Coral Larvae Dispersal

The ASV trajectory during larvae dispersal at Loomis reef is shown in Fig. 6. Green dots indicate suitable substrate according to the on-board substrate classification model, while red dots denote unsuitable substrate for larvae release. The two “Octopus” sites are manual coral dispersal deployments. The total manual deployments (across Watson and Loomis reefs) covered an area of ∼50 m$^2$. Conversely, the FloatyBoats operated mostly autonomously to release coral larvae over 200 m$^2$ at Watson’s reef, and 890 m$^2$ at Loomis reef, achieving 21.8 times more coverage compared to manual deployments during the same time period.

The performance of the on-board substrate classifier in terms of the percentage of area covered by the ASV and the amount of larvae used is shown in Table II. The ground truth was obtained by manually labelling the images recorded during dispersal. The model was compared to a hypothetical case of constantly pumping larvae, whereby all larvae released over unsuitable substrate would be considered wasted. The on-board model correctly identified suitable substrate with a success rate of 98.8% on Loomis and 98.7% on Watson, with less than 1.13% missed events, and less than 0.1% wasted larvae. Using the classifier to regulate dispersal resulted in significantly less wasted larvae over sparse reefs (e.g. Loomis). While still wasting less larvae than the constant pump, the classifier was less impactful on dense coral-cover reefs (e.g. Watson).

| Table II: Percentage of Area Covered by the ASV |
|-----------------------------------------------|
| Loomis Reef | Suitable Substrate (%) | Unsuitable Substrate (%) | Missed Event (%) | Wasted Larvae (%) |
| Ground truth | 46.85 | 53.15 | N/A | N/A |
| Constant pump | 46.85 | N/A | N/A | 53.15 |
| On-board model | 46.27 | 53.06 | 0.58 | 0.09 |
| Watson’s Reef | | | | |
| Ground truth | 90.41 | 9.59 | N/A | N/A |
| Constant pump | 90.41 | N/A | N/A | 9.59 |
| On-board model | 89.28 | 9.49 | 1.13 | 0.10 |
significant numbers of larvae, especially for "sparse" reef persal was automatically regulated using an on-board real-easily transportable ASV was presented. Coral larvae dis-scale coral reef restoration. A reconfigurable, lightweight, insights and operational approaches developed for ASVs to deployment sites.
The successful self-guided assembly and transfer training by this person then went on to train others. Fig. 7 shows non-technical expert in 10 minutes how to operate the ASV app. We employed transfer training, where we trained one fully assembled by non-technical experts using only the ASV guidance only by the ASV app. (right) A single non-technical expert with only 10 minutes ASV training transfer trains others. Fig. 7: ASVs being assembled by non-technical experts (left) guided only by the ASV app. (right) A single non-technical expert with only 10 minutes ASV training transfer trains others during the 2021 Philippines deployments.

C. Mapping

Using the images collected from the FloatyBoat’s camera, high-resolution 3D reconstructions of the reef systems can be generated. An example from Loomis Reef is shown in Fig. 6.

D. Robot Transfer Training

In the Philippines deployment, FloatyBoats were successfully assembled by non-technical experts using only the ASV app. We employed transfer training, where we trained one non-technical expert in 10 minutes how to operate the ASV and this person then went on to train others. Fig. 7 shows the successful self-guided assembly and transfer training by non-technical experts. These operators successfully operated the ASVs for spawn collection and larvae deployment at two deployment sites.

V. CONCLUSIONS

This paper has provided an overview of some design insights and operational approaches developed for ASVs to scale coral reef restoration. A reconfigurable, lightweight, easily transportable ASV was presented. Coral larvae dispersal was automatically regulated using an on-board real-time benthic substrate classification model, which conserved significant numbers of larvae, especially for “sparse” reef systems. Multiple FloatyBoats were successfully used across several reefs with 21.8 times more reef coverage than manually deployed reef restoration projects. Lastly, transfer training was demonstrated to promote operation of FloatyBoats for non-technical experts. Combined, this work has demonstrated the role autonomous systems can have in scaling reef conservation.

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