Data Correlation and Comparison from Multiple Sensors over a Coral Reef with a Team of Heterogeneous Aquatic Robots

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Abstract. This paper presents experimental insights from the deployment of an ensemble of heterogeneous autonomous sensor systems over a shallow coral reef. Visual, inertial, GPS, and ultrasonic data collected are compared and correlated to produce a comprehensive view of the health of the coral reef. Coverage strategies are discussed with a focus on the use of informed decisions to maximize the information collected during a fixed period of time.

1 Introduction

In this paper we consider the use of an ensemble of disparate robotic subsystems for data collection on a tropical coral reef. By using multiple different mobile sensing systems, we can achieve advantages in terms of data coverage and diversity over what can be achieved by single or multiple homogeneous systems, due to the ability of different systems (with different intrinsic costs) to fill gaps in the overall information profile of the ecosystem being examined.

Coral reefs are a critical part of the marine ecosystem and support a rich diversity of life with consequent economic value and social amenity. However, sea surface temperatures have increased over the past few decades, resulting in widespread coral bleaching at an ever-increasing rate. Projected increases in global temperatures of $2 - 4.5°$C by 2100 [1] indicate that mass coral bleaching events are likely to become an annual phenomenon by 2050. The widespread mortality of corals following mass bleaching events reduces the structural complexity of reefs – eliminating the three dimensional habitat, which is critical in maintaining diversity and sustainable populations of coral-reef fish communities; see Fig. 1. The first step in mitigating this degradation is to be able to observe and measure it.

Despite the importance of coral reef ecosystems, spatial and temporal dynamics of coral bleaching events are poorly understood. Most surveys of coral bleaching have been conducted using either human divers or remote sensing

Fig. 1. Representative photographs of the decline in coral reefs due to coral bleaching.

(satellite imagery), but these approaches are fundamentally limited in scale or definition. Satellites are able to cover large spatial scales, tens of square meters to square kilometers, and approximate percentage of coral cover, however, they are unable to resolve fine-scale ecological changes (centimeters to meters) of individual corals. *In situ* measurement by divers can provide such data, but at limited spatial scales (< 1 km^2) and at high cost. Automating the task of surveying an area will be extremely valuable; for example, collecting data over time and thus monitoring the health status of individual corals and the reef in general. Earlier work on multi-robot monitoring has focused on targeted data acquisition with the guidance of a marine biologist, and not on extended coverage [2] or data fusion between heterogeneous assets.

Aquatic robots provide a novel solution to the fundamental problem of large-scale precise coverage, and represent a viable approach to quantifying the extent of fine-scale coral bleaching and reef structural complexity, for long periods of time (days to weeks), and most importantly, at comparatively low cost. There are four critical research problems in better understanding coral reef health: 1) monitoring of individual coral with respect to bleaching and structural complexity; 2) quantifying changes in coral bleaching and structural complexity over time; 3) using these measures to assess reef and reef ecosystem health, and 4) to predict reef health under various scenarios. This paper describes ongoing research to help addressing the first two problems, while eventually gathering the data necessary to help address the third and fourth. More specifically, in this paper we use a combination of several classes of robotic assets to jointly survey a coral reef in the Caribbean Sea. Each class of vehicle provides complementary operational characteristics, sensing modalities, and time-scale of operations.

2 Technical Approach

Given the large spatial extents of coral reefs, it is impossible to sample everywhere at very high resolution with short-term deployment (hours) robotic assets. Moreover, many monitoring efforts have serious limitations not only in personnel, but in the resources necessary to operate a monitoring effort. We seek to examine the utility of persistent vehicles, which may provide a sparse sampling of the environment, to inform sampling missions to be executed by shorter-duration vehicles with high-resolution sensor packages.

In this paper, we examine the utility of a heterogeneous fleet of aquatic robots to cooperatively assess large-scale aquatic ecosystems, with a specific

(a) (b) (c)

Fig. 2. The different vessels used in the proposed approach (a) Drifting sensor node; (b) Kingfisher Autonomous Surface Vehicle; (c) EcoMapper Autonomous Underwater Vehicle.

focus on representing the responses of coral reef ecosystems to climate change. We approach this problem through a unique blend of persistent aquatic sampling, and vision-based sensing. The flotilla consists of six, low-cost, passive floating sensors (*drifters*) shown in Fig. 2(a), an Autonomous Surface Vehicle (ASV) shown in Fig. 2(b), and an Autonomous Underwater Vehicle (AUV) shown in Fig. 2(c). The drifters employ a monocular camera to gather image data over the reef. The ASV is equipped with a downward-looking, stereo camera, and has the ability to navigate to any chosen location. The AUV collects a range of water quality data (e.g., temperature, pH, salinity, dissolved oxygen, etc.) and gathers side-scan sonar data. This paper focuses on the *image* data products from each of the vehicles and compares them against to each other to understand the viability of such a setup for informed path planning. The extension to include water quality data fused with image and sonar data to underpin intelligent sampling is part of future work.

Visual Mosaic from Drifting Nodes

A set of inexpensive drifters has been developed to collect visual, inertial, and GPS data over moderate periods of deployment. They operate together as a passive sensor network and can be deployed manually for interaction with each other or with other vehicles. Similar drifters have been used in several research projects in marine data collection and ocean observation [3–7]. The drifters used here are different from most used previously in that they collect image data using downward-looking cameras. Currently their operation has been limited during deployments to eight hours based on the installed battery and resource allocation to track them over longer periods. The power consumption is minimal, and can easily be extended to multiple day deployments by installing a larger battery. These drifters are based on the Raspberry PI 2 computing unit and camera, and they are equipped with an inertial measurement unit (IMU) and GPS sensor. One of the main objectives of these drifters was to model Lagrangian water dynamics, by tracking the motion of a body of water [8] over long distances. The ability to collect visual data enabled the use of these drifters in a coral reef monitoring function [9]. The motion of the drifting sensor nodes at the surface includes a significant amount of bobbing from local wave action, as they are not stabilized in pitch or roll; see Fig. 2(a). Consequently each drifter rotates off the vertical by $30° - 45°$, thus expanding the regular field of view (FoV) of the camera of 60° to more than 120°. In addition, the slow Lagrangian motion of the drifters results in multiple images of the same area taken from the slightly different positions, allowing for a more robust multi-view reconstruction from the monocular camera. A modular visual pipeline framework based on OpenCV has been implemented to create patches of visual mosaics. In addition, according to the specific datasets, it is possible to choose different feature detection algorithms, descriptors, and feature matching algorithms. Augmenting vision with inertial data enables the recovery of the drifter's attitude and discarding of the images with sharp rotations that could result in loss of tracking. Being geo-referenced, the large amount of visual data collected is cross-referenced with the data collected from the other assets.

Data Collection from Other Vehicles

The ASV employed in this research is the Clearpath Kingfisher ASV [10]. This vehicle is equipped with GPS, IMU and a downward-looking, stereo GoPro camera. The AUV employed in this research is the YSI EcoMapper [11]. This vehicle is equipped with a water quality sonde, GPS, IMU, compass, side-scan sonar and upward- and downward-looking Doppler Velocity Loggers. Conversely to the operation of the drifters, these two vehicles control their own motion and navigate to specific locations rather than drift. For this research, both vehicles conducted a regular, lawnmower-type sampling strategy over the area of interest to ensure complete coverage and maximal data overlap, see Fig. 3. A primary focus of this research is to examine and fuse the information gathered to reduce the sampling burden on the short-deployment vehicles (ASV and AUV) while providing a persistent sampling presence and maximizing coverage of *important* regions within a reef environment.

Coverage Strategies

An important feature of an anytime algorithm, and in particular the coverage algorithm used by our ASV is to visit the areas of interest in decreasing order of value. This becomes significant when the task is to collect data in limited time and efficient complete coverage [12] is not possible, especially with uncertain deadlines as may occur in the presence of currents (which impact power consumption and efficiency) and variable weather. After the long-term assets (drifters) have collected enough information, the short-term assets, i.e., ASV and AUV, travel to select locations to collect additional information. A selective coverage algorithm with the behavior of choosing the salient regions to examine first is tested using the ASV [13]. This algorithm is value-iteration-based, which covers the entire region of interest, but in a prioritized fashion. The selective coverage algorithm assumes an underlying distribution for the phenomenon that needs to be modeled and builds an off-line trajectory to cover the high probability regions first, while simultaneously reducing the travel time and energy consumption. In the case of coral monitoring, the actual depth map is utilized as an input distribution to cover the shallow regions first, thus making sure the coral-populated areas are fully covered before the time constraint is reached.

One fundamental assumption made here is that, in a given area, the corals exist at shallower depths than the sand; an assumption based on observations during field trials of the specific deployment location, and input from experts in marine robotics. Based on this assumption, covering the shallower regions would provide a good coverage of the corals in the selected region.

Data Comparison and Fusion

Comparison of the collected heterogeneous data, potentially taken at different times, requires alignment and/or registration between the datasets. This has proven to be a difficult problem for large underwater datasets [14] as growth of algae and coral significantly change their appearance over time, as well as the presence of lighting differences and different data modalities.

After testing multiple different image registration techniques, including feature-based matching and Zernike moments for image recognition [15], FAB-MAP [16] was selected to recognize places based on their appearance. In particular, in the domain considered in the paper, preliminary experiments showed that the combination of STAR-SURF as a feature detector and descriptor extractor had better results in terms of number of detected features; see also the work of Quattrini Li et al. [17]. Images randomly selected from the drifters and the ASV were used for creating the training dataset to build the visual vocabulary.

3 Experiments

An area in the Folkestone Underwater Park and Marine Reserve, Barbados, was selected for deploying three heterogeneous, data-collecting assets; six drifters were randomly placed over a shallow area over multiple deployments, a Kingfisher ASV and EcoMapper AUV executed the coverage strategies described in the previous section. Figure 3 shows the region covered by each asset, and the overlapping regions covered by the three vessels. The total area is approximately 100 m x 100 m, and experiments were carried out during different days over a period of one week. Over the course of the experiments one of the drifters went missing, and was never recovered.

4 Results

Images with resolution of 640×480 were captured by the camera mounted on each of the drifters. The cameras operated at 10 FPS with a field-of-view of $\sim 60°$. The Kingfisher ASV collected stereo and monocular images using GoPro cameras mounted at the bottom of the vessel. Sonar data were collected with a Starfish Side-Scan sonar attached to a YSI EcoMapper AUV. The sonar operates at a frequency of 450 kHz, and has a range of 1 m - 100 m, with a vertical beam width of 60°. Given an average height of 5 m over the survey area, the sonar swaths were approximately 8.7 m. A sample of the different data resulting from the three vessels is presented in Fig. 4.

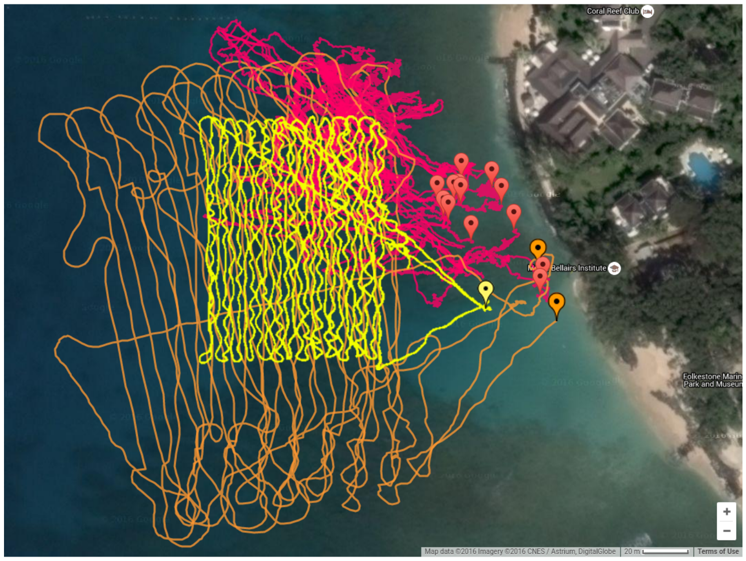
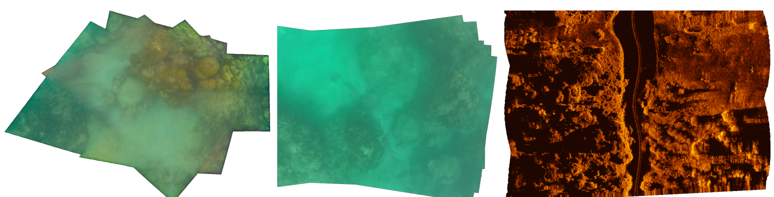


Fig. 3. The GPS traces of the three different kinds of vessels: Drifters red, ASV yellow, AUV orange.



(a) (b) (c)

Fig. 4. Data collected from the different assets (a) A mosaic patch from images of the drifter showing a coral; (b) Kingfisher ASV; (c) EcoMapper SONAR.

The drifters, even being deployed over multiple hours and days, covered a comparatively smaller area than the other vessels. This is due to the fact that they move passively, being carried by ocean currents. During the particular deployment reported here, strong surge caused the drifters to spend a significant amount of time *trapped* near the shore.

Examining and comparing the data products of the drifters and the ASV, it is possible to observe the lower camera quality of the drifter. The higher resolution of the images from the ASV and its stability in terms of rotation compared to the drifters provide a better stitched mosaic; see Figure 5. FAB-MAP was able to match some of the images from the two vessels covering the same area. Figure 6 shows a sample of images from the ASV (left) and drifters (right) that matched with the probability of association reported on the arrows. Corals have a very distinctive appearance, and the images from the two different vessels are able to match over most regions containing corals in the images. However, false positives can occur because of similar structure appearing underwater. Note that

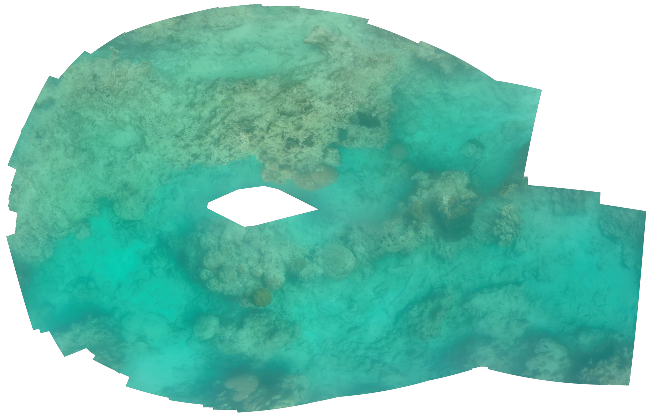


Fig. 5. Mosaic from a section of the Kingfisher's trajectory.

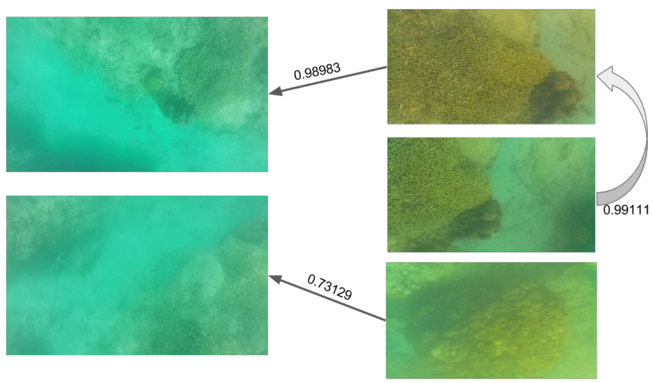
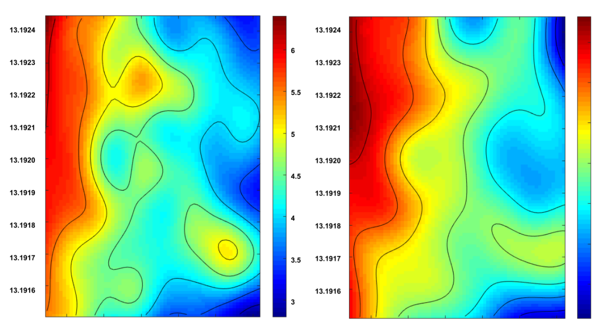


Fig. 6. The image matches between the images from kingfisher and the drifter that were reported by FAB-MAP.



(a) (b)

Fig. 7. Depth maps generated by interpolating the altitude measurements collected by two vehicles: (a) from Kingfisher robot (b) EcoMapper. The color-bars indicate the depth in meters.

the distance of the GPS associated to the related images is 5 m for the correct matched images, while about 30 m for the mismatched images.

Relating the data coming from the sonar and the cameras however did not provide the expected results, as a variety of techniques for aligning the images were proven unsuccessful.

In Figure 7, depth maps generated by the by interpolating the point measurements of the depth collected by ASV and AUV using Gaussian Processes are shown. The point measurements provided by the sonar pingers mounted on the two vessels gave a good estimate of depth over the area, producing similar maps.

Figure 8 shows the coverage trajectory followed by the robot, using the value-iteration-based method described above. The robot strategy covers the region such that the information rich areas are covered first. Thus maximizing information gain in minimum time.

5 Discussion and Experimental Insights

From the experiments carried out in the Caribbean Sea, the following experimental insights emerged.

- The drifters have a very low impact in the environment allowing them to record undisturbed marine life at a very close distance; see Fig. 9 where a short-fin Atlantic squid is recorded floating under the drifter at close range.
- Given the limited range and limited controllability of the drifters, enhancing the capabilities of these assets will be a first priority; particularly their ability to move vertically in the water column. From the preliminary data collected, they show great promise by providing the right type of data and persistence in the environment.
- Images collected by low-resolution and high-resolution cameras can be used to recognize the same places. This corroborates the idea of using a low-cost persistent vessel to inform the other vehicles about areas of interest where to sample. In addition, the images synchronized with GPS information can be used to localize AUVs underwater, where GPS information is denied. However, more work need to be done to post-process the images so that they can be recognized. A reliable place recognition module is necessary because GPS information can have significant error obstructing the high-resolution mapping of a specified area.
- The data that can be extracted from cameras and from the sonar, although they might look similar, are of a different kind and the difference in terms of coverage, resolution, and feature recognition does not allow currently for reliable alignment. Future work will focus on correlating features between these two sensing modalities.
- We used a selective coverage technique which selectively chooses the locations with high information to visit based on an underlying prior. This approach reduced the distance traveled to collect data by 48% compared to traditional methods such as repeated linear transects [13].

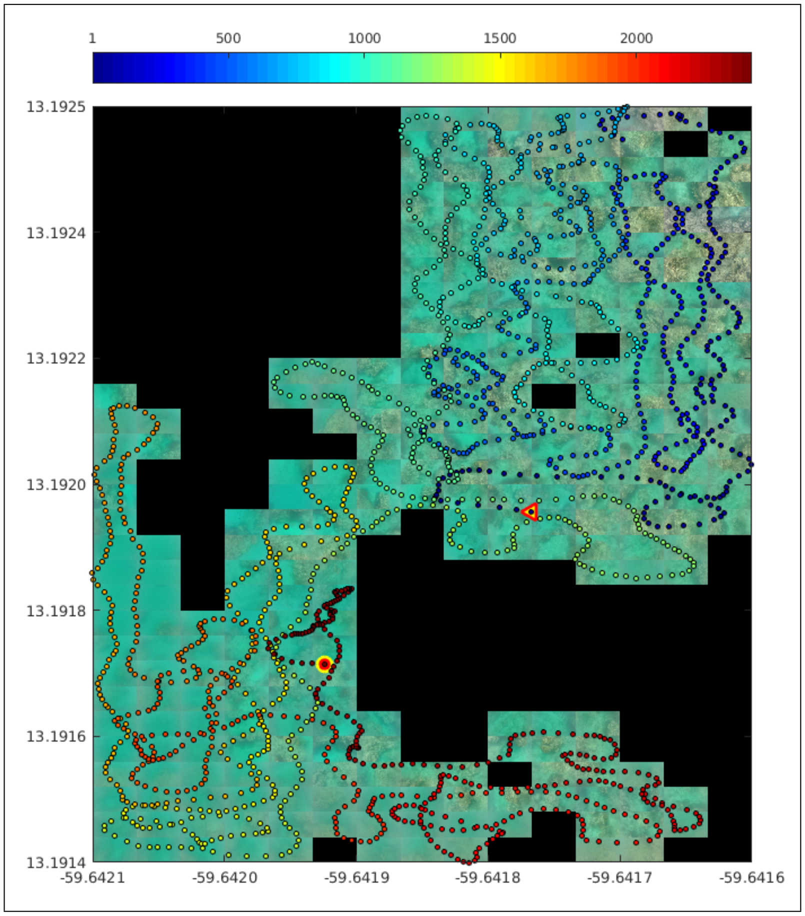


Fig. 8. Selected images from the coverage. The dotted line on the image shows the coverage trajectory of the Kingfisher robot. The color-bar indicates the time in seconds. Triangle and the circle indicate the start and end points of the path respectively.

6 Conclusions and Future Works

We have shown the use of three different types of vessels, with a specific focus on their data products. This analysis introduces new research areas, including coordinated planning of the vessels and handling communication constraints, so that large-scale coral reef assessment can be enabled.

Given long-term assets, ongoing work will build on the concept of *controlled drift* developed by Smith et al. [18, 7]. Specifically, a general desired trajectory can be achieved by using known and/or predicted ocean currents. Directly related to the areas where coral reefs exist, these platforms can operate in dynamic, coastal environments, as well as confined regions, e.g., embayments, and navigate between pre-designated waypoints.

Fig. 9. A longfin squid in an image captured by a drifter.

Given the capabilities of the long term assets and the possibility to align data from the different vessels, informed viewpoint planning could be used for a complete 3D reconstructions of coral reefs. The concept of finding an optimal viewpoint based on maximal information gain has been widely studied in the perception and manipulation communities [19–21]. In these communities, the problem is referred to as the Next-Best View (NBV) problem. The primary challenge of mission adaptation using online viewpoint planning is that the optimization constraints, specifically an overall time constraint, pose an NP hard problem (similar to the traveling salesman problem). Starting from the work of McKinnon et al. [22, 23], in which highly accurate 3D reconstructions of branching coral with complex geometry were computed, future work extends the NBV problem by computing the views that minimize camera reprojection error over the entire scene. Relaxation of the optimization constraints combined with an innovative planning strategy based on Gaussian Processes will compute a feasible path for an AUV.

Some other research directions that are worth future investigations are:

- A central question is to qualify the gains from utilizing different assets for different data collection modalities. Specifically, over a shallow reef, does the persistence of the drifters outweigh the speed of the EcoMapper?
- Supposing that all assets are collecting data simultaneously, we are interested in what communication capabilities between the devices would be useful.
- Based on experience, the drifters tend to *drift* away, understandably. We would like to investigate the problem of drifter collection via a surface vehicle. What kind of control/communication is necessary on-board the drifters in order to ensure that no drifter is *lost*?

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