Autonomous Underwater Vehicle–Assisted Surveying of Drowned Reefs on the Shelf Edge of the Great Barrier Reef, Australia

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Received 8 May 2009; accepted 7 June 2010

This paper describes the role of the autonomous underwater vehicle (AUV) Sirius on a research cruise to survey drowned reefs along the shelf edge of the Great Barrier Reef in Queensland, Australia. The primary function of the AUV was to provide georeferenced, high-resolution optical validation of seabed interpretations based on acoustic data. We describe the AUV capabilities and its operation in the context of the multiple systems used in the cruise. The data processing pipeline involved in generating simultaneous localization and mapping–based navigation, large-scale, three-dimensional visualizations, and automated classification of survey data is briefly described. We also present preliminary results illustrating the type of data products possible with our system and how they can inform the science driving the cruise. © 2010 Wiley Periodicals, Inc.

1. INTRODUCTION

In late 2007 a scientific expedition set off to survey drowned reefs along the shelf edge of the Great Barrier Reef (GBR) in Queensland, Australia (Webster, Beaman, Bridge, Davies, Byrne, et al., 2008). The GBR is the largest and best-known coral reef ecosystem in the world, with the Great Barrier Reef Marine Park (GBRMP) covering an area of approximately 344,000 km². Owing to logistical and technological restrictions, the vast majority of research on the GBR has occurred on shallow-water reefs less than 30 m deep. However, these reefs represent only 10% of the area of the GBRMP; and deepwater reef systems along the outer edge of the shelf therefore represent an extensive but largely unexplored habitat.

Drowned reefs on the edge of continental shelves or drop-off zones of oceanic islands have been recognized from many different areas of the world. Investigations off Barbados (Fairbanks, 1989), Hawaii (Webster, Clague, Riker-Coleman, Gallup, Braga, et al., 2004), Papua New Guinea (Webster, Wallace, Silver, Potts, Braga, et al., 2004), and more recently Tahiti (Camoin, Yasufmi, & McInroy, 2005) have confirmed the significance of these reefs as unique archives of abrupt global sea-level rise and climate change. Similar structures occur along the GBR, having been observed in the regions of Hydrographers Passage, Ribbon Reef (Davies & Montaggioni, 1985; Harris & Davies, 1989; Hopley, 2006; Hopley, Graham, & Rasmussen, 1996), Flora Passage, Bowl Reef, and Viper Reef (Beaman, Webster, & Wust, 2008; Hopley et al., 1996). The drowned reefs of the GBR may reflect a complex history of growth and erosion during lower sea levels and are now capped by reef material from the last deglaciation (Beaman et al., 2008). These reefs likely record a unique archive of abrupt climate changes and may provide insights into how the GBR responded to periods of environmental stress. As such, they have direct relevance for environmental managers tasked with protecting and managing the GBR.
with predicting how the GBR might respond to future climate change scenarios.

Although these drowned reefs have the potential to provide critical information on the course of sea-level and climatic history of eastern Australia, they have also been shown to support important biological communities referred to as mesophotic coral ecosystems (MCEs). Studies from locations such as Hawaii (Kahng & Kelley, 2007) and American Samoa (Bare, Grimshaw, Rooney, Sabater, Fenner, et al., 2010) have revealed that MCEs contain unique ecological communities. Because they lie beyond the depths accessible to traditional assessment techniques such as SCUBA diving, MCEs remain poorly studied, particularly compared to shallow-water coral reef ecosystems.

Recent technological advances such as the development of autonomous underwater vehicles (AUVs) have allowed scientists to explore MCEs in more detail. AUVs provide the ability to collect large quantities of high-resolution, georeferenced data and therefore represent an important tool for understanding the ecology of MCEs. In this study, data collected by an AUV are used to investigate MCEs at four sites within the GBRMP from 50–150-m depths. The key objectives for the cruise reported on here were to do the following:

• improve our understanding of the relationship between the structure, composition, and spatial distribution of drowned and modern reefs
• investigate any variations within the succession of drowned shelf edge reefs
• characterize the biological communities associated with these areas

To carry out these objectives, the study used high-resolution multibeam swath bathymetry, subbottom profiling, AUV-based stereo imaging, and rock dredge sampling, thereby providing an unparalleled view of the spatial distribution and morphologic details of the drowned reefs. The primary role of the AUV Sirius was to collect georeferenced optical imagery to provide validation of interpretations made from sonar multibeam surveys as well as subbottom profiling. The AUV provided optical imagery to assist in providing crucial baseline data about the modern substrates, habitats, and biological communities that characterize these poorly studied shelf environments. This paper describes the AUV system and its operation in the context of the cruise objectives. The data processing pipeline involved in generating simultaneous localization and mapping (SLAM)-based navigation and large-scale, three-dimensional (3D) visualizations of the seafloor is outlined. We also examine the performance of image-based classification of habitats based on labels derived from annotated images provided by an ecologist. We present results illustrating the type of data products that can be produced with such a system and examine how it can inform the science driving the cruise.

The remainder of this paper is organized as follows. Section 2 describes the various methods used to characterize the submerged reefs, including a description of the AUV, and Section 3 provides an overview of the algorithms used for constructing high-resolution representations of the seafloor and associated visualization and classification tools. Section 4 shows results from the AUV and how they relate to data collected by shipborne instruments as well as to the overall cruise objectives. Finally, Section 5 provides conclusions and discusses ongoing work.

2. STUDY METHODS

The science party approached the problem of surveying drowned shelf reefs using multiple sampling/sensing methods suited to the cruise objectives. Broad-scale mapping was used to confirm whether the reefs are consistent geomorphic features and to define patterns of past reef growth. Sites for targeted dredging, subbottom profiling, and AUV imaging were then selected for detailed study of particular features. All activities were undertaken during a 21-day cruise aboard the RV Southern Surveyor, Australia’s Marine National Facility (CSIRO MNF RV Southern Surveyor, 2008).

2.1. Ship-Based Seafloor Mapping

The primary sampling method used on this cruise involved ship-based seafloor mapping of four study sites along the Queensland margin (Figure 1(a)), where the approximate locations of submerged reefs were known. Detailed multi-beam bathymetric and backscatter (seafloor reflectivity) surveys using the ship’s Simrad EM300 were used to help determine their spatial distribution, depth, and morphology. These data established whether the submerged reefs were regionally significant features with consistent depths, as well as their relationship with shelf width and slope angle and finer scale bottom features. Subbottom profiling using the shipboard Topas PS-18 subbottom profiling sonar and a sparker towed seismic array provided information as to whether shelf edge reefs were built up or the surroundings were eroded away (erosional/constructional features) and estimates of the thickness and character of sediments between the succession of drowned reefs (Webster, Davies, Beaman, Williams, & Byrne, 2008).

2.2. AUV Surveys

A second sampling method used on the cruise involved the collection of targeted, high-resolution seafloor imagery using an AUV to validate the interpretations of the ship-based sonar data. Although a towed camera sled is traditionally used for optical characterization (Barker, Helmond, Bax, Williams, Davenport, 1999), an AUV-based approach offers improved image quality (through improved altitude control), precise positioning, and the ability to operate over
very rough bottoms. Typically the AUV will operate at lower speeds than a sled so that coverage is reduced, but in the case of optical ground truthing this tends to be compensated by the ability to target specific bottom features.

AUVs are becoming significant contributors to modern oceanographic research, increasingly playing a role as a complement to traditional survey methods. A nested survey design strategy is observable in most practical uses, in which broadscale sensing helps guide the deployment of the high-resolution imaging AUV, which in turn informs further sampling. Large, fast-survey AUVs can provide high-resolution acoustic multibeam and subbottom data by operating a few tens of meters off the bottom, even in deep water (Grasmueck, Eberli, Viggiano, Correa, Rathwell, et al., 2006; Henthorn, Caress, Thomas, McEwen, Kirkwood, et al., 2006; Marthiniussen, Vestgard, Klepaker, & Storkersen, 2004; McEwen, Caress, Thomas, Henthorn, & Kirkwood, 2006). High-resolution optical imaging requires the ability to operate very close to potentially rugged terrain. For example, the Autonomous Benthic Explorer (ABE) has helped increase our understanding of spreading ridges, hydrothermal vents, and plume dynamics (Yoerger, Jakuba, Bradley, & Bingham, 2007) using both acoustics and vision. The Seabed AUV is primarily an optical imaging AUV used in a diverse range of oceanographic cruises, including coral reef characterization (Singh, Armstrong, Gibes, Eustice, Roman, et al., 2004). Recently, the related AUVs Puma and Jaguar searched for hydrothermal vents under the artic ice (Kunz, Murphy, Camilli, Singh, Eustice, et al., 2008).

The University of Sydney’s Australian Centre for Field Robotics (ACFR) operates an oceangoing AUV called Sirius capable of undertaking high-resolution, georeferenced survey work (Williams, Pizarro, Mahon, & Johnson-Roberson, 2008). Sirius is part of the Integrated Marine Observing System (IMOS) AUV Facility, with funding available on a competitive basis to support its deployment as part of marine studies in Australia. This platform is a modified version of a midsize robotic vehicle called SeabED built at the Woods Hole Oceanographic Institution (Singh, Can, Eustice, Lerner, McPhee, et al., 2004). This class of AUV has been designed specifically for relatively low-speed, high-resolution imaging and is passively stable in pitch and roll. The submersible is equipped with a full suite of oceanographic sensors (see Table I and Figure 2).

The AUV was programmed to maintain an altitude of 2 m above the seabed while traveling at 0.5 m/s (1 kn approx.) during surveys. Missions lasted from 2 to 4 h, with the AUV surveying transects across drowned reef and interreefal areas to collect data that would allow for the assessment of the substrate types and character of the modern epibenthic assemblages associated with shelf edge reefs. In addition to 2-Hz stereo imagery and multibeam data, the AUV’s onboard conductivity/temperature (CT) and Ecopuck fluorometers sampled the water column, establishing the present-day oceanographic conditions on the shelf edge.

2.3. Dredging and Grab Sampling

The final sampling method employed during this cruise involved the collection of dredged rock samples from the tops of the shelf edge reefs and grab sampling of sediment at selected sites. The detailed bathymetric and optical surveys provide well-characterized and georeferenced target sites in each study area to obtain rock and sediment samples using rock dredges. These dredges were towed parallel to

Figure 1. Documenting drowned reefs on the GBR: (a) the ship track taken during the research cruise showing the four survey locations selected (Webster, Davies, et al., 2008) and (b) preliminary multibeam profiles showing the drowned reefs (Beaman et al., 2008).
Figure 2. (a) The AUV Sirius being retrieved after a mission aboard the RV Southern Surveyor and (b) internal component layout.

Table I. Summary of the Sirius AUV specifications.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Depth rating: 800 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>2.0 m (L) x 1.5 m (H) x 1.5 m (W)</td>
</tr>
<tr>
<td>Mass</td>
<td>200 kg</td>
</tr>
<tr>
<td>Maximum speed</td>
<td>1.0 m/s</td>
</tr>
<tr>
<td>Batteries</td>
<td>1.5 kWh Li-ion pack</td>
</tr>
<tr>
<td>Propulsion</td>
<td>Three 150 W-brushless dc thrusters</td>
</tr>
<tr>
<td>Navigation</td>
<td>TCM2 compass/tilt sensor integrated into DVL</td>
</tr>
<tr>
<td>Attitude</td>
<td>Digiquratz press. sensor</td>
</tr>
<tr>
<td>Depth</td>
<td>RDI 1,200-kHz navigator DVL</td>
</tr>
<tr>
<td>Velocity</td>
<td>RDI navigator</td>
</tr>
<tr>
<td>Altitude</td>
<td>TrackLink 1,500 HA</td>
</tr>
<tr>
<td>USBL</td>
<td>Ashtech A12</td>
</tr>
<tr>
<td>Optical imaging</td>
<td>Prosilica 12-bit, 1,360 x 1,024 change-coupled device (CCD) stereo pair</td>
</tr>
<tr>
<td>Lighting</td>
<td>Two 4-J strobe</td>
</tr>
<tr>
<td>Separation</td>
<td>0.75 m between camera and lights</td>
</tr>
<tr>
<td>Acoustic</td>
<td>Imagenex DeltaT 260 kHz</td>
</tr>
<tr>
<td>Multibeam sonar</td>
<td>Imagenex 852 675 kHz</td>
</tr>
<tr>
<td>Obstacle avoidance</td>
<td></td>
</tr>
<tr>
<td>Tracking and communications</td>
<td></td>
</tr>
<tr>
<td>Radio</td>
<td>Freewave RF modem/Ethernet</td>
</tr>
<tr>
<td>Acoustic modem</td>
<td>Linkquest 1,500-HA integrated modem</td>
</tr>
<tr>
<td>Other sensors</td>
<td>Seabird 37SBI</td>
</tr>
<tr>
<td>Clorophyll-A and turbidity</td>
<td>Wetlabs FLNTU Ecopuck</td>
</tr>
</tbody>
</table>

It is interesting to consider the relative strengths of the AUV and dredging operations in support of the study objectives. Unlike dredging, the AUV georeferenced imagery maintains the spatial relationships of observed seafloor features. Furthermore, sampling using dredging may introduce bias toward things that actually break off when a tow sled is dragged along the seafloor. The AUV imagery on the other hand can be analyzed for substrate and epibenthic cover at scales from subcentimeters to kilometers. However, recovering samples from these drowned reefs is instrumental in conclusively determining the age and composition of these structures and identifying modern benthic species inhabiting these areas (and potentially observed in the imagery). The AUV and dredging operations therefore provide complementary data to support the study objectives. In Section 4 we provide an example of a dive in which the AUV imagery was used to identify dense aggregations of brittlestars, which were later sampled using a grab sampler to facilitate species identification.
3. AUV NAVIGATION AND HABITAT MAPPING

This section presents a brief overview of techniques being used to recover detailed seabed maps based on the stereo imagery and navigation data available to the vehicle. It also describes our approach to automated classification of the imagery to help manage the volume of data being collected.

3.1. Simultaneous Localization and Mapping

Georeferencing the data collected by the AUV requires a suitable technique to estimate the vehicle’s pose throughout the dive. Navigation underwater is challenging because electromagnetic signals in water attenuate strongly with distance, precluding the use of absolute position observations such as those provided by global positioning system (GPS). Acoustic positioning-based systems (Yoerger et al., 2007) can provide absolute positioning but typically at lower precision than that provided by the environmental instruments onboard the AUV (i.e., cameras and sonars). Recent work has demonstrated methods that use the sensor data collected by the vehicle to aid in the navigation process and ensure that poses are consistent with observations of the environment. SLAM is the process of concurrently building a map of the environment and using this map to obtain estimates of the location of the vehicle. The SLAM algorithm has seen considerable interest from the mobile robotics community as a tool to enable fully autonomous navigation (Dissanayake, Newman, Clark, Durrant-Whyte, & Csobra, 2001; Durrant-Whyte & Bailey, 2006).

Early work in the deployment of the SLAM algorithm in reef environments has been reported following trials with the ACFR’s unmanned underwater vehicle Oberon and the AUV Sirius operating on the GBR in Australia (Williams & Mahon, 2004). This work laid the foundation for 3D reconstructions of these highly unstructured environments. Related work at the Woods Hole Oceanographic Institution has also examined the application of SLAM (Eustice, Singh, Leonard, & Walter, 2006; Roman & Singh, 2007) and structure from motion (SFM) (Pizarro, Eustice, & Singh, 2003) methods to data collected by remotely operated vehicles (ROVs) and AUVs.

Our current work has concentrated on efficient, stereo-based SLAM and dense scene reconstruction suitable for creating detailed maps of survey sites. Methods for stereo vision motion estimation and their application to SLAM in underwater environments have been proposed (Mahon, 2008; Mahon, Williams, Pizarro, & Johnson-Roberson, 2008). These techniques are based on the visual augmented navigation (VAN) technique (Eustice et al., 2006). In the VAN framework, the current vehicle state is estimated along with a selection of past vehicle poses, leading to a state estimate vector of the form

$$\hat{x}^+(t_k) = \begin{bmatrix} \hat{x}_{11}^+(t_k) \\ \vdots \\ \hat{x}_{1n}^+(t_k) \\ \hat{x}_{2}^+(t_k) \\ \hat{x}^+_n(t_k) \end{bmatrix}$$

(1)

where $\hat{x}_{1}^+(t_k)$ is the posterior estimate of the current vehicle states $x_v(t_k)$ at time $t_k$ and $\hat{x}^+_n(t_k) = [\hat{x}_{11}^+(t_k), \ldots, \hat{x}_{1n}^+(t_k)]^T$ is a vector of trajectory states consisting of $n$ past vehicle pose estimates. In this implementation, the vehicle state is modeled using the full six-degree-of-freedom pose and associated velocities of the vehicle relative to a local navigation frame defined at the start of the mission such that

$$x_v(t_k) = \begin{bmatrix} ^nP_v(t_k) \\ ^n\Psi_v(t_k) \\ ^v\nu_v(t_k) \\ \omega_v(t_k) \end{bmatrix}$$

(2)

with $^nP_v(t_k)$ representing the position of the vehicle in the navigation frame, $^n\Psi_v(t_k)$ representing the Euler angles of the vehicle in the navigation frame, $^v\nu_v(t_k)$ representing the velocity of the vehicle in the local vehicle frame, and $\omega_v(t_k)$ representing the local body rotation rate.

The covariance matrix has the form

$$P^+(t_k) = \begin{bmatrix} P_{PP}^+(t_k) & P_{PV}^+(t_k) \\ P_{VP}^+(t_k) & P_{VV}^+(t_k) \end{bmatrix}$$

(3)

In the information form, the filter maintains the information matrix $Y^+(t_k)$, which is the inverse of the covariance matrix

$$Y^+(t_k) = [P^+(t_k)]^{-1}$$

(4)

and the information vector $\hat{y}^+(t_k)$, which is related to the state estimate by

$$\hat{y}^+(t_k) = Y^+(t_k) \hat{x}^+(t_k)$$

(5)

The VAN information vector has the form

$$\hat{y}^+(t_k) = \begin{bmatrix} \hat{y}_{11}^+(t_k) \\ \vdots \\ \hat{y}^+_n(t_k) \end{bmatrix}$$

(6)

and the information matrix is

$$Y^+(t_k) = \begin{bmatrix} Y_{PP}^+(t_k) \\ Y_{PV}^+(t_k) & Y_{VV}^+(t_k) \end{bmatrix}$$

(7)

The VAN estimation process uses the standard extended information filter three-step prediction, observation, and update cycle. The filter process and observation model parameters used in this case are shown in Table II.

\(^1\)We use the notation of Gelb (1996) and denote the estimate using the _, the posterior using _, and the prior using _.
Table II. AUV Sirius navigation filter parameters.

<table>
<thead>
<tr>
<th>Process noise</th>
<th>Sensor</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>X, Y velocity</td>
<td>1.0 m/s²</td>
<td></td>
</tr>
<tr>
<td>Z velocity</td>
<td>0.75 m/s²</td>
<td></td>
</tr>
<tr>
<td>Roll, pitch rate</td>
<td>0.2 deg/s²</td>
<td></td>
</tr>
<tr>
<td>Heading rate</td>
<td>0.5 deg/s²</td>
<td></td>
</tr>
<tr>
<td>Observation</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.1.1. Prediction

The vehicle states are assumed to evolve according to a process model of the form

\[ \mathbf{x}_v(t_k) = \mathbf{f}_v(\mathbf{x}_v(t_{k-1})) + \mathbf{w}(t_k). \]  

where the vehicle state estimate is modeled using a constant velocity model \( \mathbf{f}_v \) and \( \mathbf{w}(t_k) \) is an error vector from a zero-mean Gaussian distribution with covariance \( \mathbf{Q}(t_k) \). Direct observations of the vehicle velocity over ground in the local vehicle reference frame are provided by the Doppler velocity log (DVL) as an observation to the filter.

When propagating the vehicle states to a new timestep with a prediction operation, the previous vehicle pose is kept in the state vector if it records the location where a stereo pair of images was acquired. Maintaining such poses allows loop-closure observations produced from vision data to be applied to the filter. When propagating the filter forward from the time of a vehicle depth, attitude, velocity, or ultra short baseline (USBL) observation, the previous vehicle pose is marginalized from the state vector (Mahon, 2000) is performed to calculate initial estimates of the feature positions relative to the stereo rig, and a re-descending M-estimator (Maronna, Martin, & Yohai, 2006) is used to calculate the relative vehicle pose hypothesis that minimizes a robustified registration error cost function. Any remaining outliers with observations inconsistent with the motion hypothesis are then rejected. Finally, the maximum likelihood relative vehicle pose estimate and covariance are then calculated from the remaining inlier features. An example set of stereo image pairs and the visual features used to produce a loop-closure observation are presented in Figure 3.

The observation of previous pose \( i \) relative to the current vehicle pose is estimated using the compound transformation that relates the two poses. This estimate is compared against the maximum likelihood relative vehicle pose estimate:

\[ \mathbf{z}_{vis}(t_k) = \begin{bmatrix} v_{x_i} & v_{y_i} & v_{z_i} & v_{\phi_i} & v_{\theta_i} & v_{\psi_i} \end{bmatrix}^T. \]  

3.1.2. Observation

Observations are assumed to be made according to a model of the form

\[ \mathbf{z}(t_k) = \mathbf{h}(\mathbf{x}(t_k)) + \mathbf{v}(t_k), \]  

in which \( \mathbf{z}(t_k) \) is an observation vector and \( \mathbf{v}(t_k) \) is a vector of observation errors with covariance \( \mathbf{R}(t_k) \). The difference between the actual and predicted observations is the innovation

\[ \mathbf{v}(t_k) = \mathbf{z}(t_k) - \mathbf{h}^{\prime}(\hat{\mathbf{x}}(t_k)). \]  

Velocity

Observations of the vehicle velocity in the local body frame are provided by the vehicle’s DVL. This device provides measurements of the speed over ground of the vehicle at distances up to 45 m from the seafloor:

\[ \mathbf{z}_{dvl}(t_k) = \begin{bmatrix} v_x & v_y & v_z \end{bmatrix}^T. \]  

Depth

Measurements of depth are inferred from measurements provided by the vehicle’s pressure sensor:

\[ \mathbf{z}_{depth}(t_k) = \begin{bmatrix} z \end{bmatrix}. \]  

Attitude

The vehicle’s RDI navigator DVL includes an integrated compass with roll and pitch sensor. Given the design of the vehicle, the roll and pitch are relatively stable once the vehicle is underway:

\[ \mathbf{z}_{att} = \begin{bmatrix} \phi_v & \theta_v & \psi_v \end{bmatrix}^T. \]  

Visual Loop Closures

Loop-closure observations are created using a six-degree-of-freedom stereo vision relative pose estimation algorithm (Mahon, 2008). The SIFT algorithm (Lowe, 1999) is used to extract and associate visual features, and epipolar geometry is used to reject inconsistent feature observations within each stereo image pair. Triangulation (Hartley & Zisserman, 2000) is performed to calculate initial estimates of the feature positions relative to the stereo rig, and a re-descending M-estimator (Maronna, Martin, & Yohai, 2006) is used to calculate a relative pose hypothesis that minimizes a robustified registration error cost function. Any remaining outliers with observations inconsistent with the motion hypothesis are then rejected. Finally, the maximum likelihood relative vehicle pose estimate and covariance are then calculated from the remaining inlier features. An example set of stereo image pairs and the visual features used to produce a loop-closure observation are presented in Figure 3.

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Ultra Short Baseline Positioning

Observations of range and bearing between the support ship and the vehicle are provided by a USBL positioning system. Observations of ship position and attitude available from the ship’s navigation instruments are combined with the measured position of the sonar head (in this case mounted in a moon pool near the center of the ship) to provide an estimate of the transceiver location. The sensor provides a measurement of the range \( R \) and bearing \( \beta \) between
3.1.3. Update

The innovation is used to update the information vector and matrix:

\begin{align}
\hat{y}^+ (t_k) &= \hat{y}^- (t_k) + i (t_k), \\
Y^+ (t_k) &= Y^- (t_k) + I (t_k), 
\end{align}

in which

\begin{align}
i (t_k) &= \nabla_x h (t_k) R^{-1} (t_k) [v (t_k) + \nabla_x h (t_k) \hat{x}^- (t_k)], \\
I (t_k) &= \nabla_x h (t_k) R^{-1} (t_k) \nabla_x^T h (t_k),
\end{align}

where \( \nabla_x h (t_k) \) is the Jacobian of the observation function with respect to the vehicle states.

The SLAM filter uses the information form due to the efficiency of observation updates. Methods to efficiently recover pose estimates and covariances from the information vector and matrix are detailed in Mahon (2008) and Mahon et al. (2008). These methods allow the data collected by the vehicle to be processed while at sea, allowing the scientists to examine the georeferenced imagery and associated seafloor models between dives. Examples of SLAM being applied to data collected during this cruise are presented in Section 4.

3.2. Seafloor 3D Reconstructions

Although SLAM recovers consistent estimates of the vehicle trajectory, the estimated vehicle poses themselves do not provide a representation of the environment suitable for human interpretation. A typical dive will yield several thousand georeferenced overlapping stereo pairs. Although useful in themselves, single images make it difficult to appreciate spatial features and patterns at larger scales. We have developed a suite of tools to combine the SLAM trajectory estimates with the stereo image pairs to generate 3D meshes and place them in a common reference frame (Johnson-Roberson, Pizarro, Williams, & Mahon, 2010). The resulting composite mesh allows a user to quickly and easily interact with the data while choosing the scale and viewpoint suitable for the investigation. Spatial relationships within the data are preserved, and users can move from a high-level view of the environment down to very detailed examination of individual images and features of interest within them. This is a useful data exploration tool for the end user to develop an intuition of the scales and distributions of spatial patterns within the seafloor habitats.

The process used to generate 3D reconstructions can be broken down into the following main steps as shown in Figure 4:

1. Data Preprocessing. The primary purpose of the preprocessing step is to partially compensate for lighting and wavelength-dependent color absorption. This allows improved feature extraction and matching during the next stage.

2. Stereo Depth Estimation. Extracts two-dimensional (2D) feature points from each image pair, robustly proposes correspondences, and determines their 3D position by triangulation. The local 3D point clouds are converted into individual Delaunay triangulated meshes.

3. Mesh Aggregation. Places the individual stereo meshes into a common reference frame using SLAM-based poses described in the preceding section. The system
fuses the meshes into a single mesh using volumetric range image processing (VRIP) (Curless & Levoy, 1996). The total bounding volume is partitioned so that standard volumetric mesh integration techniques operate over multiple smaller problems while minimizing discontinuities between integrated meshes. This stage also produces simplified versions of the mesh to allow for fast visualization at broad scales.

4. **Texturing.** The polygons of the complete mesh are assigned textures based on the overlapping imagery that projects onto them. Lighting and misregistration artifacts are reduced by separating images into spatial frequency bands that are mixed over greater extents for lower frequencies (Burt & Adelson, 1983).

5. **Visualization.** Some AUV missions have upward of 10,000 pairs of images, which expands to hundreds of millions of vertices when processed to generate the stereo meshes. It is simply intractable to load all of these data directly into memory. To view the data we use a discrete paged level of detail scheme (Clark, 1976), in which several discrete simplifications of geometry and texture data are generated and stored on disk. Level of detail (LOD) in 3D meshes allows viewing extremely large models with limited computational bandwidth by reducing the complexity of a 3D scene in proportion to the viewing distance or relative size in screen space.

Section 4 and the multimedia extensions present examples of detailed 3D surface models derived from data collected during a number of dives completed during this cruise.

### 3.3. Habitat Classification

Although the visualization of detailed 3D reconstructions improves our ability to understand the spatial layout of seafloor features, further analysis and interpretation of the data gathered during a dive is required to address tasks such as habitat characterization and monitoring. This analysis stage is typically performed by human experts, which limits the amount and speed of data processing (Holmes, Niel, Radford, Kendrick, & Grove, 2008). It is unlikely that machines will match humans at fine-scale classification any time soon, but machines can now perform preliminary, coarse classification to provide timely and relevant feedback to assist human interpretation and focus attention on features of interest. We are developing an image-based habitat classification and clustering system to facilitate the analysis of the large volumes of image data collected by the AUV (Pizarro, Colquhoun, Rigby, Johnson-Roberson, & Williams, 2008; Pizarro, Williams, & Colquhoun, 2009).

We have adapted a state-of-the-art object recognition system (Nister & Stewenius, 2006) to recognize and classify marine habitat imagery based on labeled examples (Pizarro et al., 2008). These approaches are inspired in the “bag of words” technique to document recognition and have been demonstrated on challenging tasks (Philbin, Chuim, Isard, Sivic, & Zisserman, 2007; Sivic & Zisserman, 2003). The techniques represent an image (document) as a collection of visual features (words), which are further grouped using probabilistic topic models. A topic model $\theta$ in a collection of images (documents) is a probability distribution $\{p(w|\theta)\}_{w \in V}$ of visual features (words) $w$ over the vocabulary set $V$. It represents a semantically coherent topic with high-probability words collectively suggesting a semantic theme. As such, topics form an intermediate level of abstraction and can be considered a form of dimensionality reduction that aids human interpretation. Instead of...
modeling an image as a bag of words, the image is represented as a mixture of topics.

A set of training documents is used to build a vocabulary of topics so that query documents can be described by the frequency of occurrence of all the topics in the vocabulary set. In the case of images, these approaches typically use local features that select distinctive regions and describe them in a manner that is robust or invariant to changes in scale and orientation. The approach finds the images in the training set that are closest to the query image. If we can assign a class (habitat) label to each training image, it is possible to assign a class to a query image based on the class of the closest training image. Section 4 examines the effectiveness of using these visual topics to classify images based on labeling provided by a human expert. The performances of a number of a common classifiers are compared on this habitat classification task.

4. RESULTS

This section presents results of these activities, illustrating how the navigation information, 3D reconstructions, and classified imagery complement data collected by other instruments during the cruise. Four sites along the extent of the GBR, as shown in Figure 1(a), were selected for detailed bathymetric mapping, AUV seafloor imaging, dredging, and grab sampling to determine substrate composition during the cruise (Webster, Davies, et al., 2008). Figures 5 and 6 show bathymetric maps and AUV dive profiles of three of the four study sites. These maps were used to identify potential AUV dive sites and the location of subbottom profiling, grab sampling, and dredging operations. Higher resolution versions of these maps are being used to study the relict reef sites in more detail.

Over the course of the 3-week voyage, the AUV was deployed at nine locations, undertaking both overlapping grid surveys of particular features and cross-shelf transects to document the variability in benthic habitats as a function of depth. The AUV imagery shows a variety of benthic communities and substrates that include red algae–encrusted fossil rock, thriving hard and soft coral, gorgonians (sea whip or fan), sponge communities, and Halimeda (green algae). Table III provides a summary of the dives undertaken during the course of the cruise. As can be seen, the vehicle covered in excess of 26 linear kilometers and collected more than 115,000 images. Figures 5(c), 5(d), 6(c),

Figure 5. Bathymetric maps of the Noggin Pass and Viper Reef study sites. (a) and (b) Relatively low-resolution bathymetric maps generated during the cruise. (c) and (d) Details of the dives overlaid on the local bathymetry. The circled numbers correspond to dive IDs shown in Table III.
and 6(d) show profiles of the eight missions flown by the vehicle, illustrating the variety of dive profiles undertaken and the flexibility in mission planning afforded by the AUV. Each dive was targeted at a particular benthic feature and was designed with respect to the bathymetric information available. For example, dives 5, 7, and 8 each featured relatively dense overlapping grids, with dives 7 and 8 designed to survey habitats at different depths in a single dive. On the other hand, dives 4, 6, and 9–11 were designed to cover more ground and encompass a greater variety of benthic

Table III. Dive summary.

<table>
<thead>
<tr>
<th>Dive ID</th>
<th>Start time (UTC)</th>
<th>Dur. (h)</th>
<th>Lat.</th>
<th>Long.</th>
<th>Max D. (m)</th>
<th>Dist. (m)</th>
<th>Av. alt. (m)</th>
<th>Stereo pairs</th>
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<td>−15.378</td>
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<td>174</td>
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<td>808</td>
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<td>4</td>
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<td>97.8</td>
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<td>1.94</td>
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<tr>
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<td>146.566</td>
<td>64.2</td>
<td>1,518</td>
<td>2.08</td>
<td>6,735</td>
</tr>
<tr>
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<td>98.5</td>
<td>1,143</td>
<td>2.01</td>
<td>5,295</td>
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<td>06/10/07 00:11</td>
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<td>147.7</td>
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<td>2.03</td>
<td>25,958</td>
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<td>147.0</td>
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<td>2.07</td>
<td>15,916</td>
</tr>
<tr>
<td>10</td>
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<td>1:45</td>
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<td>2,676</td>
<td>1.97</td>
<td>12,660</td>
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<tr>
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<td>12/10/07 04:21</td>
<td>3:00</td>
<td>−19.868</td>
<td>150.460</td>
<td>70.2</td>
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<td>2.04</td>
<td>21,349</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>115,780</td>
</tr>
</tbody>
</table>
habitats. Dive 2, undertaken at the Ribbon Reef site, was unusual in that a fault with the vehicle software prevented the vehicle from completing its intended mission and is not shown here. Dives 1 and 3 were engineering dives aimed at ensuring the vehicle operations prior to the scientific missions and are also not shown here.

The flexibility with which the vehicle could be programmed allowed for a tight coupling between other data being collected, such as the ship-borne multibeam, and the design of the AUV dive profiles. This allowed the scientists to plan missions targeting particular features based on bathymetric maps being generated by the ship’s sonar. During deployments, the vehicle was programmed to complete a particular dive profile designed according to the desired mission objectives. The vehicle operated completely autonomously of the ship, and its progress was monitored using the USBL mounted on the ship’s hull. An acoustic link allowed updated estimates of the vehicle state and diagnostic information to be transmitted to the ship. The USBL observations were also communicated to the vehicle but were not fused into the vehicle estimate during the deployment. The vehicle’s estimated state while underway was based on the dead-reckoning information provided by the DVL, attitude, and depth sensor.

The following sections describe three of the dives in more detail, demonstrating the improvement in navigation estimates achievable using our SLAM techniques and illustrating how the AUV imagery complements other data collected during the cruise.

4.1. Dive 5: Overlapping Grid Survey

Dive 5 at Noggin Pass, shown in Figure 5(c), consisted of a 100 × 100 m overlapping grid survey. This dive was positioned in approximately 60 m of water over an area characterized by suspected ancient shoals. The vehicle covered approximately 1.5 km of linear travel, achieving a maximum depth of 65 m. The bottom was largely composed of sandy substrate, with a number of relict coral outcrops supporting modern coral and Halimeda.

A comparison of the estimated trajectories produced by dead reckoning and two SLAM filters for this deployment is shown in Figure 7. The filters integrate the DVL velocity observations with measures of depth, heading, roll, and pitch. The dead-reckoning filter is not given access to imagery and is therefore not able to correct for drift that accumulates in the vehicle navigation solution. In contrast, loop closures identified in the imagery allow for this drift to be identified and for the estimated vehicle path to be corrected. In the first instance, the filter is provided with all of the USBL observations collected during the mission. This can be considered the best navigation estimate we can generate for these deployments. The second filter uses the USBL observations only during the descent and ascent portions of the dive. This allows the mission to be georeferenced for comparison with the full solution but relies on visual loop closures to maintain the consistency of the pose estimates during the dive. Although the absolute position of the SLAM estimates differ, the general shapes of the trajectories are consistent with a constant offset related to the georeferencing of the resulting dive profile. A third filter that uses dead reckoning only is not consistent with the loop closures identified during the dive. This can be seen in the close-up portions of the figure. This survey included more than 6,500 image pairs, and loop-closure observations were identified at each crossing using both SLAM filters, shown by the magenta and cyan lines joining estimated poses.

Figure 8 shows a comparison of the 2σ standard deviation uncertainty bounds in the estimates for the three filters. As can be seen, the uncertainty in the dead-reckoned position grows during the course of the mission until the USBL observations are fused at the end of the run. The loop closures allow the SLAM filters to limit the growth of uncertainty in the vehicle position. For each of the SLAM filters, both the vehicle covariance during the run and the covariance of the final pose estimates are shown. As can be seen, all of the poses achieve an uncertainty equivalent to the smallest pose uncertainty of the vehicle during the dive. This is a result of the correlations between estimated vehicle poses that are maintained by the filter.

Figure 9(a) illustrates the improvement in consistency of the estimates afforded by the pose-augmented SLAM solution. In this case, the best estimate of the vehicle pose is provided by the filter that integrates all of the USBL observations. Although this is not an entirely independent source of ground truth, the covariance plots suggest that the filter is providing estimates with an uncertainty on the order of a few meters. Taking the difference between the dead-reckoned estimate of vehicle trajectory and this filter solution shows that there are significant differences in the estimated vehicle pose during the course of the dive (on the order of 15 m in some instances). The estimated vehicle poses provided by the SLAM filter, on the other hand, show a difference of less than 5 m throughout the dive relative to the full solution, and this offset is constant for all poses except in the immediate vicinity of the USBL observations. This is largely a result of the number of loop closures available to constrain the vehicle poses in this case and effectively translates into the residual difference in the georeferenced pose of the two solutions. We can also examine the consistency of the projection of the loop-closure feature positions using the estimated vehicle poses associated with the loop closures. The SLAM filters are designed to minimize this error for features that are part of the loop-closure constraints. Figure 9(b) shows histograms of the $L^2$ norm of the 3D registration errors for the case of the full SLAM solution (including USBL), the filter that integrates USBL only at the start and end of the dive, and the dead-reckoning filter. As can be seen, the 3D registration errors...
Figure 7.  (a) Comparison of dead-reckoning and SLAM vehicle trajectory estimates for grid survey 5. The full SLAM solution (including all USBL observations recorded during the dive) is shown in red with triangle markers, the SLAM trajectory with USBL used only at the start and end of the dive is shown in black with circle markers, and the dead-reckoning estimates with USBL observations also available only at the start and end of the dive are shown in green with plus sign markers (the markers are shown at every 10th image position). (b) A close-up of a portion of the dive showing the visual loop closures in more detail. The magenta and cyan lines connect vehicle poses that have had a loop closure applied for the full and limited USBL SLAM solutions, respectively. The camera is mounted approximately 0.8 m forward of the navigation frame origin, resulting in the loop-closure pose estimates being offset from the crossover itself. (c) Notice that the relative positions of the transects are consistent between the SLAM solutions but that the crossover in the dead-reckoning solution is significantly closer to the corner. This would result in an error in the resulting seafloor model.
Figure 8. The 2σ standard deviation bounds for the full SLAM solution (including all USBL observations), the solution that fuses USBL only at the beginning and end of the trajectory, and the dead-reckoning covariances.

Figure 9. (a) The difference between the full SLAM solution (including USBL observations throughout) and SLAM trajectory that uses USBL only at the start and end of the dive is shown in black, and the difference between the full SLAM solution and dead-reckoning estimates is shown in green. (b) Histograms of the $L^2$ norm of the 3D position errors for loop-closure features for the case of the full SLAM solution (including USBL), the filter that integrates USBL only at the start and end of the dive, and the dead-reckoning filter.
The innovations for the observations can also be examined to verify the consistency of the filter estimates. Figure 10 shows the innovations and associated $2\sigma$ innovation covariances for the measurements of velocity, attitude, depth, and range/bearing. The innovations appear white and are bounded by the innovation covariance. There are a number of outliers in the USBL data that are rejected by the filter. Notice that the USBL observations are not available to the SLAM filter but the innovations are still consistent at the end of nearly an hour without external observations.
to the SLAM filter but the innovations are still consistent at the end of nearly an hour without external observations.

A 3D overview of the dive profile is show in Figure 11(a), and Figures 11(b) and 11(c) show details of two reef outcrops, highlighting the seafloor structure encountered by the vehicle during this deployment. Some of these outcrops were up to 6 m in height and appeared to be covered in modern coral, sponge, and algae, illustrating the importance of these structures for modern reef organisms. These communities have not been extensively studied because of their location beyond traditional SCUBA diving depths.

4.2. Dive 9: Cross-Shelf Transect

Figure 12 shows a detailed view of one of the AUV dive sites at Hydrographers Passage (dives 9 and 10) overlaid on the bathymetry. The objective of the pair of dive tracks visible in this image was to assess the habitat composition on the 50-m feature and to undertake a cross-shelf transect out into deeper water. The site was selected following high-resolution bathymetric surveying to examine ancient foreshore structures. The vehicle was initially deployed over relict reefs in 50 m of water. As can be seen in Figure 12, it then traveled to the northeast over a succession of deep, relict reefs, descending to a depth of 150 m. Subbottom profiling and dredging were also undertaken in the same area. Once the vehicle was recovered, it was possible to examine the bottom composition correlated with the depths. The AUV imagery showed a number of distinct benthic habitats. These included modern reef areas in the photic zone (<80 m) covered in coral and algae, a flat sandy area along the shelf, an area between 100 and 135 m of water depth corresponding to a relict shoreline feature characterized...
by hard substrate supporting modern deepwater benthic assemblages, and a deepwater area characterized by flat sandy substrate.

We conducted an ecological analysis of a subset of the images to describe the composition of substrate types and taxonomic groups visible in every 20th image for this dive ($n = 718$). This provided a virtual quadrat (composed of a single image) at approximately 5-m intervals across the seafloor along the entire length of the transect. Data were recorded using a grading system based on estimated relative abundance of five substrate types and 14 major taxonomic groups as shown in Table IV. The scoring followed the methods of Done (1982), where 1 = <5% cover of any given substrate type, 2 = 5%–10%, 3 = 11%–30%, 4 = 30%–80%, and 5 = >80% for any substrate type in each image. Sessile benthic taxa occurred in 97% of analyzed images along the entire length of the transect. Differences in the benthic assemblages are particularly evident when the images are examined, and we were interested to investigate whether a classifier based on automatically derived image features would be capable of learning to classify the images using habitat clusters derived based on the expert input.

A K-means clustering algorithm with five groups was used to cluster the images based on the ecological abundance metrics. Figure 13 shows the dive track and depth profile of the vehicle color coded by cluster number. As can be seen, a number of distinct groupings are present within the data, corresponding to the following groups:

- **C1** corresponding to the relatively flat shelf
- **C2** occurring in the deep water where the sand was relatively smooth and unpopulated
- **C3** present on steeply sloping areas of the seabed and at a rough limestone section of seafloor at the shelf edge
- **C4** occurring at the base of slopes
- **C5** centered in the shallow reef areas

Figure 14(a) shows the mean for each of the substrate and taxa metrics in the resulting clusters. It can be seen that cluster C1, located along the shelf, is dominated by sandy substrate and benthic foraminifera. Cluster C5, on the other hand, is located in the shallow reef area and features a mix of substrate types and relatively high abundances across all taxa. The distribution of these distinct habitats is a function of the substrate as well as light available and hence depth. Figure 14(b) shows a mapping of the clusters onto the first two components of the principal components of

<table>
<thead>
<tr>
<th>Substrate</th>
<th>Taxon group</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Rough limestone</td>
<td>6. Fan gorgonian</td>
</tr>
<tr>
<td>2. Sediment-covered limestone</td>
<td>7. Other sponge</td>
</tr>
<tr>
<td>3. Rubble</td>
<td>8. Carteriospongia</td>
</tr>
<tr>
<td>5. Sand</td>
<td>10. Dendronephthya</td>
</tr>
<tr>
<td>11. Branching scleractinia</td>
<td>12. Other scleractinia</td>
</tr>
<tr>
<td>15. Halimeda</td>
<td>16. Cyanobacteria</td>
</tr>
<tr>
<td>17. Green algae</td>
<td>18. Red algae</td>
</tr>
<tr>
<td>19. Benthic foraminifera</td>
<td></td>
</tr>
</tbody>
</table>
Figure 13. (a) AUV track overlaid on underlying bathymetric model and color coded by cluster derived from substrate and taxa composition identified by an expert. (b) Corresponding depth profile color coded by cluster.

The metrics. The first two principal components account for more than 60% of the variability in the data. The clustering has resulted in groups that are well defined using these principal components, and we were interested to evaluate how well our visual topics would perform in classifying the imagery using these labels. Examples of the images corresponding to these clusters are shown in Figure 15. Figure 16 shows portions of the 3D reconstruction corresponding to this dive for each of the clusters derived based on the hand-labeled imagery.

The hand labeling of the images takes a considerable amount of time and requires an expert trained in taxonomic analysis. Automated classification approaches, on the other hand, can be run without expert input once trained and can be completed within a few hours of the completion of a dive. For the data collected during this cruise, it is simply intractable to hand label all of the imagery collected by the vehicle. We therefore used the cluster labels derived from the hand-labeled composition of the imagery to test a number of classification systems based on the visual topics describing each image as outlined in Section 3.3. We ran the classification using a number of common classifiers, including a regression tree (Breiman, Friedman, Stone, & Olshen, 1984), linear discriminant analysis (Krzanowski, 1988), K nearest neighbor (Mitchell, 1997) (with support from the five nearest neighbors), and a support vector
Figure 15. Sample images of habitat clusters derived from substrate and taxa composition.

A summary of the classification results is shown in Figure 17. The first column shows the type of classifier and the average estimation accuracy using 10-fold cross validation of the labeled data for each of the four classifiers tested. The middle column shows the confusion matrix, and the last column shows the depth profile color coded by images that are misclassified by each classifier (green is no error, and the strength of the red dots is proportional to the number of times each image is misclassified during cross validation). As can be seen, the regression tree does not perform as well as the other three classifiers tested for this problem. Images along the first slope tend to be more poorly resolved, and there appear...
to be common images that are incorrectly classified by all classifiers.

These results suggest that the visual features are able to successfully differentiate the habitat classes identified based on the substrate and taxonomic metrics assigned based on our ecological assessment. We are now developing fully automated clustering and classification systems that can provide clustering of the imagery without the need for expert input. One difficulty with such automated methods for image clustering is the ability to assign semantic meaning to the resulting clusters. We are also working to relate the habitat classification based on the AUV imagery to the underlying bathymetric data collected by the ship to facilitate the creation of broader scale habitat models.

### 4.3. Dive 11: Brittlestar Beds

Finally, we highlight the results of dive 11 in which the vehicle both surveyed a shallow portion of the reef and conducted broader scale surveys across a sandy dune field in the vicinity of Hydrographers Passage. Figure 18 shows a portion of the AUV dive track overlaid on the bathymetry, with image locations featuring aggregations of brittlestars highlighted in red. These locations are correlated with the lee side of the dunes and provide the animals with a
5. CONCLUSIONS

Properly instrumented AUVs can fill an important niche as part of multidisciplinary research cruises such as the one described here. They present a novel tool for collecting rich, high-resolution, georeferenced data sets that are complementary to more traditional shipborne measurements. In this case the imagery produced by the AUV has proven to be invaluable in providing very high-resolution, fine-scale interpretation of benthic habitat characteristics. The AUV provided a platform to obtain quantitative information on biological communities and habitats beyond the depths accessible by traditional methods.

The visual SLAM techniques have allowed us to compensate for errors in the navigation induced by dead-reckoning drift. The algorithms have been validated using large-scale data sets collected as part of a scientific expedition to survey drowned reefs. Although validating navigation systems was not the primary goal of this expedition, we have demonstrated how SLAM can be used to generate a consistent, georeferenced navigation solution suitable for creating detailed 3D models of the seafloor. These models are now being used to investigate the relationship between fine-scale seabed structure and the benthic organisms they support.

Just as important as a reliable and capable platform is the ability to quickly produce consistent and accurate
Figure 18. (a) Brittlestar locations identified in red overlaid on underlying bathymetry. Notice that the aggregations tend to correspond to the tops of the dune features (b) A portion of the 3D model of the seafloor highlighting the density of brittlestars on the dunes. This represents an area of approximately 3.0 × 1.5 m featuring hundreds of animals.

APPENDIX: INDEX TO MULTIMEDIA EXTENSIONS

A video is available as Supporting Information in the online version of this article.

ACKNOWLEDGMENTS

This work is supported by the ARC Centre of Excellence programme, funded by the Australian Research Council (ARC) and the New South Wales State Government, the Integrated Marine Observing System (IMOS) through the Department of Innovation, Industry, Science and Research (DIISR) National Collaborative Research Infrastructure Scheme, the Australian Marine National Facility, and National Geographic. RJB acknowledges a Queensland Smart Futures Fellowship for salary support. The authors would like to thank the captain and crew of the RV Southern Surveyor. Without their sustained efforts none of this would have been possible. Thanks to Peter Davies, Kate Thornborough, Erika Woolsey, Sandy Tudhope, Phil Manning, Alex Thomas, and the CSIRO techs for help and support onboard the ship. We also acknowledge the help of all those who have contributed to the development and operation of the AUV, including Duncan Mercer, George Powell, Ritesh Lal, Paul Rigby, Jeremy Randle, Bruce Crundwell, and the late Alan Trinder.

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