Autonomous Seabed Inspection for Environmental Monitoring

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Abstract We present an approach for navigating in unknown environments, while gathering information for inspecting underwater structures using an autonomous underwater vehicle (AUV). To accomplish this, we first use our framework for mapping and planning collision-free paths online, which endows an AUV with the capability to autonomously acquire optical data in close proximity. With that information, we then propose a reconstruction framework to create a 3-dimensional (3D) geo-referenced photo-mosaic of the inspected area. These 3D mosaics are also of particular interest to other fields of study in marine sciences, since they can serve as base maps for environmental monitoring, thus allowing change detection of biological communities and their environment in the temporal scale. Finally, we evaluate our frameworks, independently, using the SPARUS-II, a torpedo-shaped AUV, conducting missions in real-world scenarios. We also assess our approach in a virtual environment that emulates a natural underwater milieu that requires the aforementioned capabilities.

Keywords Path planning · Mapping · Photo-mosaics · Online computation constraints · Monitoring · Underwater environments · AUV

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1 Introduction

During the last years, there has been a growing interest on monitoring different environmental variables that permits not only to have a better understanding of our planet, but also to estimate the human impact on it. This, consequently, has propelled research in various sectors of the scientific community, but especially in the development of robotic systems, which are capable of conducting autonomously data gathering tasks in different environmental media, such as air, soil and water [1]. In this latter, for instance, most of the underwater robotics applications include an autonomous underwater vehicle (AUV) that follows a sequence of pre-calculated waypoints in order to collect data. These underwater surveys are normally conducted in a previously explored area so that the vehicle navigates at a constant and safe altitude from the seafloor. In a typical application, the vehicle uses its onboard sensors, such as multibeam and imaging sonars, to gather information that is used to build bathymetric maps (elevation maps of the seabed). These maps can be used for safe surface and sub-surface navigation, thus enabling a variety of applications, such as underwater archeology [2].

More recent applications, on the other hand, require the AUV to navigate in close proximity to underwater structures and the seafloor. Such applications are especially dedicated to imaging and inspecting different kinds of structures such as underwater boulders [3] or confined natural structures (*e.g.,* underwater caves). In some of these cases, preliminary information about the structure to be inspected, such as its location and shape, permits determining in advance a region of interest, so that a coverage path is pre-calculated, while information obtained during the inspection is used to correct online the path in order to, for instance, adapt to the real structure's shape [3]. There is, nonetheless, a group of applications in which no previous information is available or cannot be obtained autonomously. In such cases, preliminary works have been focused on gathering data to characterize such environments.

On that basis, the purpose of this paper is twofold: first, we build up on our previous work [4] a framework to endow an AUV with the capability to navigate autonomously in unknown environments while exploring the ocean floor; secondly, to build a framework that allows the construction of 3-dimensional (3D) geo-referenced photo-mosaics of the seafloor. Therefore, the use of both frameworks represents

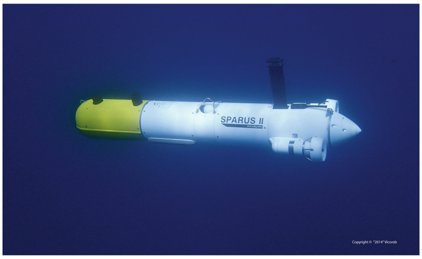


Fig. 1 SPARUS-II, a torpedo-shaped AUV.

the main contribution of this work, which endows an AUV with the capability to navigate autonomously an underwater milieu, while gathering optical information. Such information is used for building video-based 3D mosaics, which will serve as base maps for environmental monitoring of interest areas, allowing change detection of biological communities and their environment in the temporal scale, and enabling a new way to visualize the evolution of wide areas in that temporal scale. The planning and reconstruction frameworks have been tested with both synthetic and real-world scenarios using the SPARUS-II AUV (see Fig. 1).

2 Path Planning Framework

This section reviews our path planning framework for solving start-to-goal queries online for an AUV in an unknown environment (see Fig. 2) [4]. Additionally, we explain how to incorporate a criterion to maintain a desired distance to guarantee visibility constraints while conducting a mission in close proximity [5].

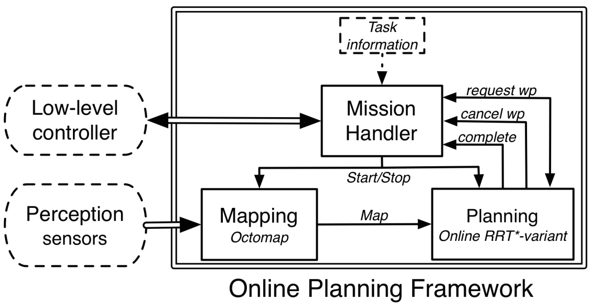


Fig. 2 Framework for online path planning with its three main functional modules and corresponding inputs and outputs [4].

2.1 Mission Handler

The *mission handler* controls the general flow of the proposed path planning framework. To ensure that the vehicle is prepared for solving and conducting a task, this module communicates with other vehicle's functional modules and verifies that navigation data is being received, perception sensors are providing valid data and vehicle's controllers are not conducting any low-level safety maneuver. When the mission has started, a bidirectional communication with the *planning* module is established. The *mission handler* requests waypoints, when required, and receives and adapts them for the vehicle's low-level controller. Additionally, the *planning* module can notify the *mission handler* to cancel ongoing waypoint requests.

2.2 Mapping

The *mapping* module incrementally builds a representation of the environment using information received from different perception sensors, such as multibeam or mechanically scanned profiling sonars, echosounders, etc. Such sensors provide range information about nearby obstacles and, combined with the vehicle navigation (position and orientation), defines the free and occupied space with respect an inertial coordinate frame. To process this information, we use an octree-based representation, named Octomap [6], which is a framework for modeling volumetric information with three main characteristics.

2.3 Planning

The *planning* module receives a query to be solved, which is specified as a start and goal vehicle configuration, as well as additional planning parameters, such as the available computing time, minimum distance to the goal, and boundaries of the workspace. This module contains a modified version of the RRT* [7], which, as any other RRT-variant, has as a main characteristic the rapid and efficient exploration of the configuration space (C-Space), but also includes the asymptotic optimality property. Finally, our modified version of the RRT* incorporates concepts of *anytime* algorithms and *lazy collision evaluation* that, together with its incremental nature, make it suitable for online (re)planning applications (see [4] for further details).

2.4 Costmap for Surveying at a Desired Distance

In addition to common challenges in images processing, visibility plays a critical role when gathering optical information in underwater environments. Having this in mind, we propose to define a costmap over the C-Space that attempts to meet the distance constraint required to guarantee visibility with respect to the inspected structure. This approach is based on our previous work, where the main objective was to maintain a desired altitude from the seafloor [5]. The cost associated to each configuration q, $0 \leq Cost \leq 100$, where 0 and 100 are the minimum and maximum cost respectively, is presented in Eq. 1. The Cost depends on the distance (d) and includes adjustable parameters. One of those parameters is the expected distance d_e to the inspected structure. Another is an admissible range of distance Δd_a, which permits to define an interval of distance in which the associate cost has its minimal value (clearly observed in Fig. 3). Finally, this cost function defines the optimization objective for the modified RRT* used in the planning module previously explained.

$$Cost(d) = \begin{cases} \left(1 - \frac{d}{d_e}\right) 100, & d < d_e - \frac{\Delta d_a}{2} \\ 0, & d_e - \frac{\Delta d_a}{2} \leq d \leq d_e + \frac{\Delta d_a}{2} \\ \left(\frac{d}{d_e} - 1\right) 100, & d > d_e + \frac{\Delta d_a}{2} \end{cases} \tag{1}$$

Nonetheless, it is important to remark that defining high-cost values to certain zones does not restrict or limit them as possible paths, but it will attempt to avoid them as much as possible. In other words, this approach is different than defining restricted areas, where the vehicle would not be allowed to move through. An example of these situations is when the only possible path coincides with the restricted zone (highest cost), in which our approach will permit that path as a valid solution.

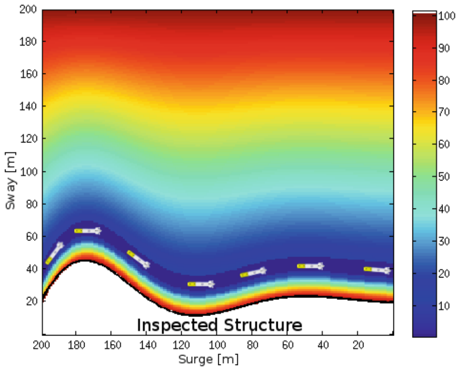


Fig. 3 Costmap projected in vehicle's X(surge)-Y(sway) plane. Dark blue indicates the zone that meets visibility constraints.

3 3-Dimensional (3D) Reconstruction Framework

While conducting an autonomous underwater mission, optical cameras continuously acquire images in order to gather information of the observed environment. Once the mission is completed, a reconstruction pipeline processes the images through a series of steps (see Fig. 4), which results is a textured 3D triangle mesh representation of the observed scene. While this is a preferable representation for visualization purposes, a smaller subset of successive steps can be conducted, if the subsequent usage of the results requires solely dense or even sparse point cloud representation, enabling the reduction in the computational cost. Different pipeline processing steps are described in the following subsections.

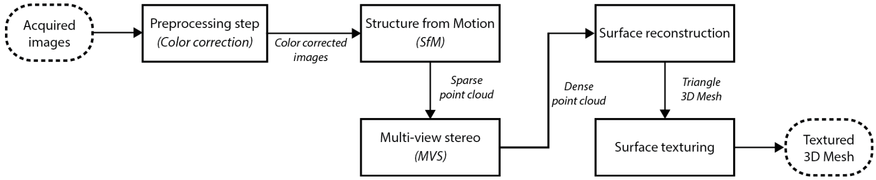


Fig. 4 3D reconstruction framework pipeline.

3.1 *Color Correction*

The acquisition of the optical images in underwater environments significantly differs from the conventional imagery, due to the specific properties of the medium. Light attenuation and scattering are the two main phenomena that strongly affect the image quality and consequently the acquisition task [8]. The progressive attenuation of the light combined with the various degrees of absorption at different wavelengths results in characteristic predominance of the blue and green color in farther objects (see Fig. 6a). As this phenomenon affects not only the ability to reconstruct a visually accurate representation of the scene, but also the quality and quantity of scale-invariant feature transform (SIFT) matchings [9] used in the subsequent steps, an automated preprocessing step is performed to ensure the color consistency. By equalizing the color contrast through contrast stretching of RGB (red, green, blue) channels, and subsequent saturation and intensity stretching of HSV (hue, saturation, value) the increment of true colors is achieved, as proposed by Iqbal *et al.* [10]. An example of a preprocessed image is shown in Fig. 6b.

3.2 *Structure from Motion*

Using the set of previously preprocessed images, the 3D information of the observed scene is obtained by the process known as Structure from Motion (SfM). The simultaneous estimate of the structure, simplified to 3D points, and the poses of the cameras, from which the images were acquired, is inferred entirely from the texture features extracted and matched across the image set.

In the proposed framework, an incremental implementation of SfM - VisualSfM [11, 12] is used, due to its efficient and reliable performance. While the algorithm enables the recovery of both extrinsic (*i.e.,* the position and orientation of the camera at the moment of the acquisition) and intrinsic (*i.e.,* focal length and radial distortions of the lens) cameras parameters, we use predetermined values for the intrinsics obtained through standard calibration procedure [13]. This significantly reduces the complexity of the problem and subsequently minimizes the possibility of wrong convergence in the process of optimization of the rest of the parameters. Additionally, all images are undistorted prior to their usage, as radial distortion introduces an additional ambiguity into SfM [14]. As a final result, an estimate of the camera poses and 3D structure in a form of sparse 3D point cloud are obtained.

3.3 Multi-view Stereo

To obtain a globally consistent dense representation of the scene, a window-based voting approach introduced by Goesele *et al.* [15] is used. Initially, the individual depth maps for each of the views are reconstructed using estimation of camera poses. This is followed by a merging step, which fuses the independent depth maps using a hierarchical signed distance fields approach of Fuhrmann *et al.* [16]. While the overlapping of certain views produces an excessive redundancy in storage and computation, the avoidance of averaging the geometry at different resolutions of the maps enables the estimation of highly detailed geometry in a form of dense 3D point cloud. Additionally, as only a small subset of neighbouring images are required for the computation of each depth map, the process is easily scalable to longer sequences and larger scenes.

3.4 Surface Reconstruction

Using a dense set of unorganized 3D points, the surface reconstruction process estimates the underlying surface in a form of a triangle mesh. As described by Kazhdan *et al.* in [17], the Poisson surface reconstruction, used in our approach, forms a unique implicit surface representation through the reconstruction of an indicator function. This is achieved by blending local contributions of implicit locally approximated functions at sets of points. As the approach assumes the normals to be known, these are computed using the connectivity information in the process of fusion of depth maps in the previous MVS step. Given the fact that Poisson method returns a closed surface, relevant information is subsequently extracted by eliminating the triangles with edges longer than certain threshold (triangles tend to increase size in non-sampled parts) [18].

3.5 Texturing

A vitally important step in providing the scientists with the realistic representation of the observed scene, is enhancing previously obtained 3D triangle mesh with a texture. Using the approach of Waechter *et al.* [19] realistic texture is computed by ensuring the photo consistency together with the minimization of the discontinuities and the visibility of seams between patches. Together with the previously described steps this enables the reconstruction of texturized 3D mesh representation of the observed scene.

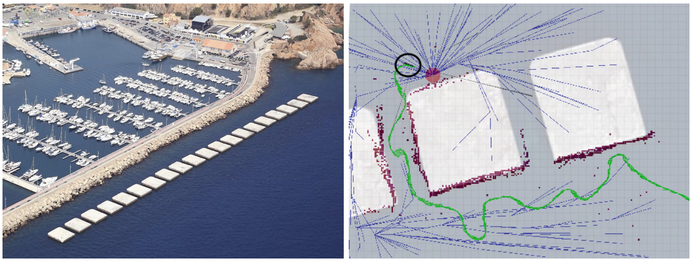
4 Results

To validate our proposed approach, we evaluate both the path planning [4] and 3D reconstruction frameworks, independently, in a real-world scenario. Additionally, we propose and demonstrate our approach suitability in a virtual scenario that emulates a natural underwater environment, which requires navigating autonomously with no previous surroundings information.

4.1 Online Mapping and Path Planning in Unknown Environments

To evaluate our path planning framework, we used the SPARUS-II AUV (see Fig. 1), a torpedo-shaped vehicle with hovering capabilities, rated for depths up to $200m$. The robot has three thrusters (two horizontal and one vertical) and can be actuated in surge, heave and yaw degrees of freedom (DOF). The vehicle is equipped with a navigation sensor suite including a pressure sensor, a doppler velocity log (DVL), an inertial measurement unit (IMU) and a GPS to receive fixes while at surface. To perceive the environment, a set of five echosounders are located within the vehicle payload (front) area. Four of them are in the horizontal plane, three are separated by 45^o, with the central one looking forward and parallel to the vehicle's direction of motion, while the fourth one is perpendicular to the central one. In order to assess the effectiveness of our approach, we used the external and open area of the harbour of Sant Feliu de Guíxols in Catalonia (Spain) as test scenario (see Fig. 5a), which is composed of a series of concrete blocks of $14.5m$ long and $12m$ width, separated by a four-meter gap with an average depth of $7m$.

In this scenario, the SPARUS-II AUV had to move amidst the concrete blocks without any previous knowledge of their location. All queries have been defined to conduct



(a) (b)

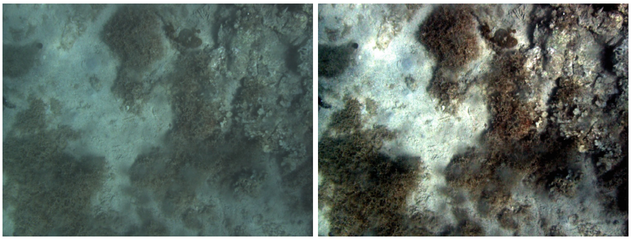
Fig. 5 (a) Experiments scenario: a breakwater structure composed of concrete blocks in the harbor of Sant Feliu de Guíxols in Catalonia, Spain. (b) the vehicle has moved through the four-meter gap between the second and third concrete block and approaches to the last waypoint.

missions with a constant depth, since most of perception sensors (echosounders) are located to cover the horizontal plane, thus the motion is restricted to a 2-dimensional (2D) task.

4.2 3D Reconstruction

To evaluate the reconstructed 3D model, a real-world dataset of images obtained using the SPARUS-II AUV during a demonstration in Breaking the Surface (BtS) 2014 (Biograd Na Moru, Croatia)[1] has been used. In the demo, the SPARUS-II conducted an autonomous mission navigating at constant depth while gathering information with onboard sensors, including a pre-calibrated optical camera oriented downwards. Images were obtained at a frequency of $4Hz$ and recovered from the AUV after the mission for offline processing. This section presents the results of a 3D reconstruction using such images.

To illustrate the possibility of such approach, the results of processing an approximately a minute long sequence containing 213 images acquired while observing a geometrically diverse scene due to the presence of rocks and underwater vegetation are presented. An example of an acquired image is shown in Fig. 6a. The predominance of blue and green tones is evident, together with the low contrast of the colors. Using color correction step, as presented in Section 6a, the true colors are enhanced as can be observed in Fig. 6b.

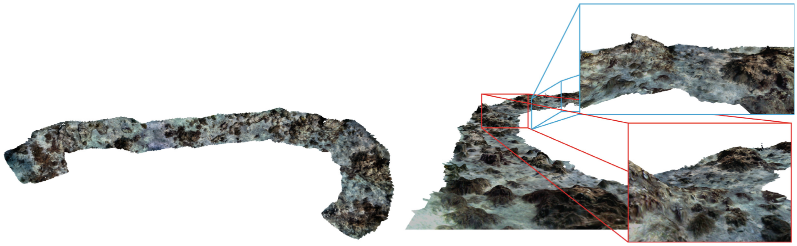


(a) (b)

Fig. 6 Example of an image acquired with a pre-calibrated optical camera oriented downwards (Biograd Na Moru, Croatia). (a) original image. (b) image after color correction.

Using the pipeline described in Section 3, the sequence of images was processed obtaining a textured 3D triangle mesh. While the data can be visualized in a standard top-down mosaic like perspective, as shown in Fig. 7a, the obtained reconstruction also permits observations from arbitrary user-defined poses, as shown with two examples in Fig. 7b.

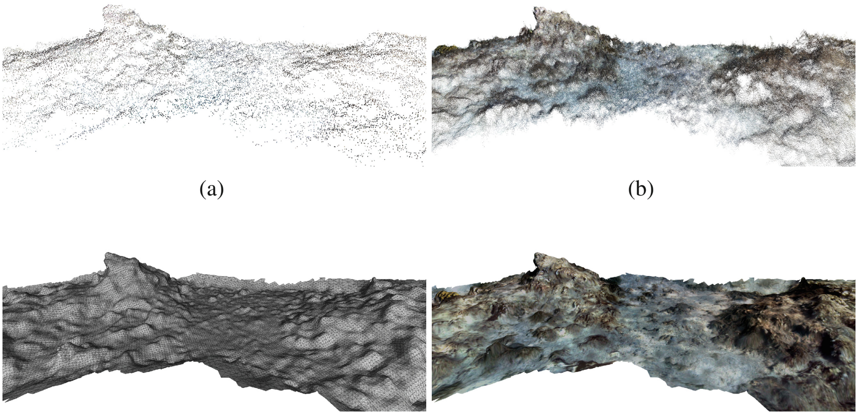
[1] https://bts.fer.hr/



(a) (b)

Fig. 7 (a) Top-down view of the reconstructed scene. (b) Arbitrary user-defined views of reconstructed scene

As aforementioned, the reconstruction process can consist of a smaller subset of successive steps, enabling the user to reduce the computational time. The intermediate results (sparse/dense point cloud, triangle mesh and textured triangle mesh) are presented in Figs. 8a - 8d.



(a) (b) (c) (d)

Fig. 8 Intermediate reconstruction results. (a) Sparse point cloud. (b) Dense point cloud. (c) Triangle mesh. (d) Textured triangle mesh.

It should be mentioned that given the fact that the reconstruction is performed solely based on the information from a set of acquired images, the area of interest should be imagined multiple times to ensure sufficient information and observation of areas which might be occluded in certain views.

4.3 Navigating Autonomously through a Natural-like Environment

SPARUS-II, as well as the other AUVs developed at the underwater vision and robotics research center (CIRS)[2], is controlled through the component oriented layer-based architecture for autonomy (COLA2) [20], a control architecture that is completely integrated with the robot operating system (ROS). Besides operating aboard real robots, COLA2 can interact with the underwater simulator (UWSim) [21], which can import 3D environment models and simulate the vehicle's sensors and dynamics with high fidelity. We used UWSim with a 3D model that emulates an underwater canyon, in which we tested our path planning framework while gathering optical images. Results validated the AUV capability to create a representation (map) of a complex and unknown environment that was used, simultaneously, to incrementally plan collision-free paths (see Fig. 9).

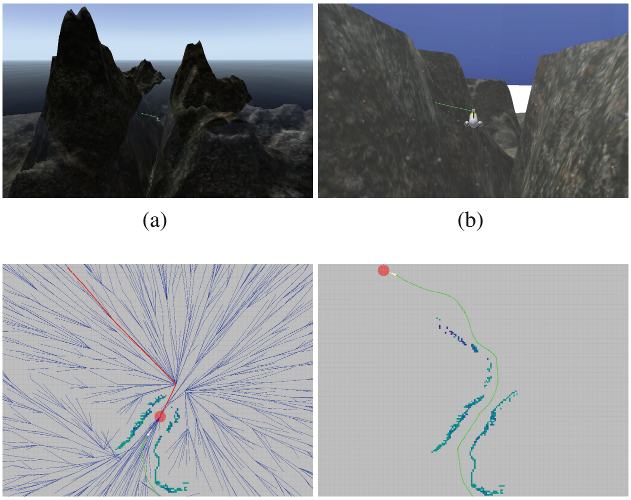

(a) (b)
(c) (d)

Fig. 9 SPARUS-II AUV in UWSim [21] conducting an autonomous mission. (a) virtual scenario that resembles an underwater canyon. (b) SPARUS-II navigates through the canyon. (c) intermediate states and resulting path of the RRT* solving the start-to-goal query. (d) SPARUS-II successfully completes the task.

[2] http://cirs.udg.edu/

5 Conclusions and Further Work

In this paper, we presented a new approach for inspecting autonomously underwater structures in close proximity to the seabed using AUVs. To do so, we proposed to use our framework for mapping and planning collision-free paths simultaneously and online, thus permitting an AUV to autonomously inspect an area of interest by acquiring optical images. Using that data, we then proposed a reconstruction framework to create 3D geo-referenced photo-mosaics, which can be used as base maps for environmental monitoring.

We validated, independently, both the path planning and 3D reconstruction frameworks in real-world scenarios. We also assessed our approach in a virtual scenario that emulates an underwater canyon, in which a simulated SPARUS-II AUV was able to navigate without previous knowledge of the surroundings while acquiring optical images. Finally, we will focus our immediate efforts to replicate this latter experiment, but now conducting the mission in an real-world underwater corridor-like (canyon) environment. Additionally, longer sequences will be used in the reconstruction process, to obtain the reconstruction of larger areas. This will permit us to validate our capability to reconstruct complex 3D environments.

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