ONLINE 3D VIEW PLANNING FOR AUTONOMOUS UNDERWATER EXPLORATION

Eduard Vidal Garcia

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Doctoral Thesis

Online 3D View Planning for Autonomous Underwater Exploration

Eduard Vidal Garcia

2019

Universitat de Girona

Doctoral Thesis

Online 3D View Planning for Autonomous Underwater Exploration

Eduard Vidal Garcia

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Doctoral Program in Technology

Supervised by:

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in fulfillment of the requirements for the degree of

Doctor of Philosophy

Certificate of Thesis Direction

Dr. Marc Carreras, member of the *Departament d'Arquitectura i Tecnologia de Computadors* of *Universitat de Girona*, and Dr. Narcís Palomeras, member of the *Departament d'Arquitectura i Tecnologia de Computadors* of *Universitat de Girona*,

Declare:

That the work entitled *Online 3D View Planning for Autonomous Underwater Exploration* presented by Eduard Vidal Garcia to obtain the degree in Doctor of Philosophy has been developed under our supervision and fulfills the requirements to obtain the International Mention.

Therefore, in order to certify the aforesaid statement, we sign this document.

Girona, October 2019

Dr. Marc Carreras

Dr. Narcís Palomeras

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List of Publications

Publications in the compendium

The presented thesis is a compendium of the following research articles:

- Marc Carreras, Juan David Hernández, **Eduard Vidal**, Narcís Palomeras, David Ribas, and Pere Ridao. "Sparus II AUV-A Hovering Vehicle for Seabed Inspection". In: *IEEE Journal of Oceanic Engineering (JOE)* 43.2 (2018), pages 344–355
Quality index: JCR2017 Oceanography, Impact Factor: 2.065, Q2.
Contributions: This publication presented the Sparus II AUV and the main motion and view planning research lines of the lab, as a solution to perform autonomous underwater tasks, such as online mapping, inspection and exploration.
Author contributions: The author wrote a substantial part of the article, and it is the main developer of the view planning (VP) results shown in the publication.

- **Eduard Vidal**, Juan David Hernández, Klemen Istenič, and Marc Carreras. "Online View Planning for Inspecting Unexplored Underwater Structures". In: *IEEE Robotics and Automation Letters (RA-L)* 99.3 (2017), pages 1436–1443
Quality index: Not indexed yet.
Contributions: This paper presented a 2-dimensional (2D) VP algorithm for autonomous underwater exploration. The algorithm iteratively plans the next-best-view (NBV) in order to fully map an unknown underwater structure. A novel characteristic of the proposed algorithm is that it is designed to ensure coverage of an unknown environment with occupancy data and with optical data simultaneously, in a single exploration mission.
Author contributions: The author of this thesis started the development of the algorithm during his masters degree, also under the supervision of Dr. Marc Carreras. The author is the main developer of the algorithm, and he was also in charge of the experimental tests performed with the Sparus II AUV. Juan David Hernández mainly helped in the start to goal planning subproblem. Klemen Istenič was in charge of the 3D reconstructions presented in the publication. Finally, the author of this thesis wrote the publication, which was reviewed by the other authors.

- **Eduard Vidal**, Narcís Palomeras, Klemen Istenič, Juan David Hernández, and Marc Carreras. "Two-Dimensional frontier-based viewpoint generation for exploring and mapping underwater environments". In: *Sensors (Switzerland)* 19.6 (2019), page 1460

Quality index: JCR2017 Instruments & Instrumentation, Impact Factor: 2.475, Q2.
Contributions: This paper presented the improvements made to the 2D exploration algorithm together with new experimental results in the Amarrador seamount. This publication fully reports the 2D algorithm, from the algorithmic details and implementation details to the experimental results.
Author contributions: The author is the main developer of the improvements made to the algorithm. He is also the main responsible of the experimental evaluation, and the writing of the article. Juan David Hernández helped in the start to goal motion planning and Klemen Istenič was in charge of the 3D reconstructions presented in the article.

- **Eduard Vidal**, Mark Moll, Narcís Palomeras, Juan David Hernández, Marc Carreras, and Lydia E. Kavraki. "Online Multilayered Motion Planning with Dynamic Constraints for Autonomous Underwater Vehicles". In: *IEEE International Conference on Robotics and Automation (ICRA)*. volume –. –. 2019, pages –
Quality index: Not a journal.
Contributions: This publication presented a motion planner to enhance the planning capabilities of the exploration algorithm. The planner is able to generate dynamically feasible paths while accounting for water currents, and its efficiency enables its use in online planning. This publication was the result of the research stay performed by the author of this thesis in the Kavraki Lab, Houston, USA.
Author contributions: The author, with help from Lydia Kavraki, Mark Moll, Marc Carreras and Juan David Hernández are the main developers of the algorithm. The author, with help from Narcís Palomeras and Marc Carreras, did the integration of the algorithm with the Sparus II AUV, and designed and performed the sea tests.

- **Eduard Vidal**, Narcís Palomeras, and Marc Carreras. "Multisensor Online 3D View Planning for Autonomous Underwater Exploration". Submitted to Journal of Field Robotics. 2019
Quality index: Submitted to JCR2017 Robotics, Impact Factor: 3.46, Q1.
Contributions: This publication presents our final results on 3-dimensional (3D) VP for autonomous underwater exploration. It extends the 2D algorithm to 3D and adds improvements in the algorithm and extensive experimental evaluation using the Girona 500 AUV.
Author contributions: The author is the main developer of the 3D VP algorithm, with ideas from the other authors. The experimental results were obtained by the main author and Narcís Palomeras.

Publications derived from this thesis

The work developed in this thesis also led to the following publications:

- **Eduard Vidal**, Juan David Hernández, Klemen Istenič, and Marc Carreras. "Optimized Environment Exploration for Autonomous Underwater Vehicles". In: *IEEE International Conference on Robotics and Automation (ICRA)*. 2018

- **Eduard Vidal**, Narcís Palomeras, and Marc Carreras. "Online 3D Underwater Exploration and Coverage". In: *AUV2018*. 2018

- **Eduard Vidal**, Juan David Hernández, Narcís Palomeras, and Marc Carreras. "Online Robotic Exploration for Autonomous Underwater Vehicles in Unstructured Environments". In: *IEEE Oceans 2018-Kobe*. 2018

- Juan David Hernández, **Eduard Vidal**, Jennifer Greer, Romain Piasco, Patrick Jaussaud, Marc Carreras, and Rafael Garcia. "AUV online mission replanning for gap filling and target inspection". In: *IEEE Oceans 2017-Aberdeen*. 2017

- Narcís Palomeras, Natàlia Hurtós, **Eduard Vidal**, and Marc Carreras. "Autonomous Exploration of Complex Underwater Environments Using a Probabilistic Next-Best-View Planner". In: *IEEE International Conference on Robotics and Automation (ICRA)*. 2019

Other publications

Parallel work at the time of this thesis led to the following publications:

- Juan David Hernández, **Eduard Vidal**, Guillem Vallicrosa, Enric Galceran, and Marc Carreras. "Online Path Planning for Autonomous Underwater Vehicles in Unknown Environments". In: *IEEE International Conference on Robotics and Automation (ICRA)* (2015), pages 1152–1157

- Juan David Hernández, **Eduard Vidal**, Guillem Vallicrosa, Èric Pairet, and Marc Carreras. "Simultaneous Mapping and Planning for Autonomous Underwater Vehicles in Unknown Environments". In: *IEEE Oceans 2015-Genova*. 2015

- Juan David Hernández, Guillem Vallicrosa, **Eduard Vidal**, Èric Pairet, Marc Carreras, and Pere Ridao. "On-line 3D Path Planning for Close-proximity Surveying with AUVs". In: *IFAC Workshop on Navigation, Guidance and Control of Underwater Vehicles (NGCUV2015)*. 2015

- Juan David Hernández, Mark Moll, **Eduard Vidal**, Marc Carreras, and Lydia E. Kavraki. "Planning feasible and safe paths online for autonomous underwater vehicles in unknown environments". In: *IEEE International Conference on Intelligent Robots and Systems (IROS)*. 2016, pages 1313–1320

- Juan David Hernández, Klemen Istenič, Nuno Gracias, Narcís Palomeras, Ricard Campos, **Eduard Vidal**, Rafael García, and Marc Carreras. "Autonomous Underwater Navigation and Optical Mapping in Unknown Natural Environments". In: *Sensors* 16.8 (2016), page 1174

- Marc Carreras, Juan David Herńandez, **Eduard Vidal**, Narcís Palomeras, and Pere Ridao. "Online motion planning for underwater inspection". In: *Autonomous Underwater Vehicles 2016, AUV 2016*. 2016

- Angelos Mallios, **Eduard Vidal**, Ricard Campos, and Marc Carreras. "Underwater caves sonar data set". In: *The International Journal of Robotics Research (IJRR)* 36.12 (2017), pages 1247–1251

- Natàlia Hurtós, Angelos Mallios, Narcís Palomeras, Josep Bosch, Guillem Vallicrosa, **Eduard Vidal**, David Ribas, Nuno Gracias, Marc Carreras, and Pere Ridao. "LOON-DOCK: AUV homing and docking for high-bandwidth data transmission". In: *IEEE Oceans 2017-Aberdeen*. Volume 2017-Octob. 2017
- Narcís Palomeras, Guillem Vallicrosa, Angelos Mallios, Josep Bosch, **Eduard Vidal**, Natàlia Hurtós, Marc Carreras, and Pere Ridao. "AUV homing and docking for remote operations". In: *Ocean Engineering* 154 (2018), pages 846–894
- Juan David Hernández, **Eduard Vidal**, Mark Moll, Narcís Palomeras, Marc Carreras, and Lydia E. Kavraki. "Online motion planning for unexplored underwater environments using autonomous underwater vehicles". In: *Journal of Field Robotics (JFR)* 36.2 (2018), pages 370–396

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Abstract

Autonomous underwater vehicles (AUVs) are currently used in many different applications, such as near-bottom mapping, manipulation or inspection. Most of the time, these tasks are planned in advance using prior information about the environment where the robot will operate. When this prior information does not exist, robotic exploration algorithms can be used so that the robot can safely discover the environment. Currently, exploration algorithms present important limitations, especially in environments with high relief, where obstacles might be present. In addition, most exploration algorithms are designed to fully explore the environment to obtain only one type of data, which it is usually occupancy data. With those algorithms, if imagery is also required, it is necessary to perform a second mission so that the robot obtains images using the map initially created. Combining these two missions into one would save time and, consequently, reduce costs.

The goal of this thesis is, therefore, to develop a robotic exploration algorithm for autonomous underwater vehicles that is capable of exploring safely unknown environments in 3D, obtaining simultaneously a grid map with the relief or shape of the environment and also a set of images that cover all the surfaces.

The presented robotic exploration algorithm works iteratively. Using the data reported by the sensors, the algorithm generates a map and automatically determines the regions to be explored next. From all the possible regions to explore, the algorithm chooses the best one and generates a viewpoint that will allow the robot to obtain information of the region of interest. To reach the selected viewpoint, the algorithm computes a safe path from the current robot configuration, taking into account the obstacles in the map.

The first part of this thesis develops a 2D exploration method for environments with high relief. Occupancy data is gathered by a scanning profiling sonar, and optical data is obtained from an underwater camera, mounted in the Sparus II AUV, a torpedo shaped robot. Then, this part continues with the development of an improved version of the algorithm, where a noise filtering strategy is proposed to remove the noise present in the sonar sensor, as it negatively affects the consistency of generated maps, which may cause the exploration algorithm to take suboptimal exploration decisions. This part also focuses on the efficiency of the implementation of the algorithm so that it can be executed fast enough for online planning. The second part of this thesis develops a start to goal motion planner to improve the planning capabilities of the exploration framework. The proposed motion planner accounts for the nonlinear dynamics of the vehicle and the water currents, and it allows to use the full range of maneuvers provided by the robot. The third part of the thesis develops a 3D exploration method. In this part, the Girona 500 AUV is used

with a multibeam sonar mounted on a pan-and-tilt device, and an underwater camera. In this part the algorithm is developed in order to improve its robustness and safety.

Finally, this thesis presents experimental results obtained with the Sparus II and Girona 500 robots. The algorithm has been tested in different scenarios located in St. Feliu de Guíxols: a harbor area, a breakwater structure, the Punta del Molar rock, and the Amarrador underwater boulder. The obtained results show that the presented algorithm is capable of guiding the robot in order to explore a completely unknown environment to obtain simultaneously an occupancy and an optical map. Using the images obtained during exploration experiments, it has been possible to create 3D reconstructions of the explored environments.

Resum

Els robots autònoms submarins s'utilitzen actualment en moltes aplicacions diferents, com per exemple en mapeig de proximitat, manipulació o inspecció. La majoria de vegades, aquestes tasques es planifiquen amb anterioritat utilitzant informació prèvia de l'entorn on el robot operarà. Quan aquesta informació prèvia no existeix, es poden utilitzar algorismes d'exploració robòtica per tal que el robot descobreixi per si mateix l'entorn de forma segura. Els algorismes d'exploració actuals presenten limitacions importants, sobretot en entorns que poden presentar molt de relleu, on el robot es pot trobar amb obstacles. A més a més, la majoria d'algorismes d'exploració estan dissenyats per obtenir un mapa complet de l'entorn amb un sol tipus de dades, que normalment són dades amb el relleu o la forma de l'entorn. Si també es volen obtenir imatges de l'entorn, amb aquests algorismes és necessari realitzar una segona intervenció per tal que el robot les obtingui a partir del mapa creat inicialment. Combinar aquestes dues intervencions en una de sola permetria estalviar temps i, conseqüentment, reduir costos.

L'objectiu d'aquesta tesi és, doncs, desenvolupar un algorisme d'exploració robòtica per a vehicles submarins autònoms que sigui capaç d'explorar de manera segura entorns desconeguts en 3D, obtenint simultàniament un mapa de graella amb el relleu o forma de l'entorn i imatges obtingudes des de poca distància que cobreixin les superfícies detectades.

L'algorisme d'exploració presentat funciona de forma iterativa. A partir de les dades que els sensors van percebent, l'algorisme genera un mapa i hi identifica, de forma automàtica, les regions que s'han d'explorar a continuació. De totes les possibles regions a explorar, l'algorisme n'escull la millor i genera un punt de vista que permetrà obtenir informació de la regió d'interès. Per tal que el robot assoleixi el punt de vista seleccionat, l'algorisme calcula un camí segur des de la posició actual del robot, tenint en compte els obstacles presents al mapa.

La primera part d'aquesta tesi desenvolupa un mètode d'exploració 2D per a entorns que presenten relleu. Les dades de l'entorn s'obtenen mitjançant un sonar perfilador i una càmera submarina, muntats al robot Sparus II, un robot amb forma de torpede. Aquesta part de la tesi continua amb el desenvolupament d'una versió millorada de l'algorisme d'exploració, on es proposa una estratègia de filtratge de soroll per eliminar el soroll present en el sonar, ja que afecta negativament la consistència dels mapes generats, i això pot provocar que l'algorisme d'exploració prengui decisions poc òptimes. Aquesta part també desenvolupa les estratègies necessàries per aconseguir que l'algorisme es pugui implementar de forma que la seva execució sigui suficientment ràpida. La segona part d'aquesta tesi desenvolupa un planificador de trajectòries per millorar les capacitats de

planificació de l'algorisme d'exploració. El planificador de trajectòries proposat té en compte la dinàmica no lineal del vehicle i els corrents d'aigua, i permet utilitzar tota la gamma de maniobres del robot. La tercera part de la tesi desenvolupa un mètode d'exploració 3D. En aquesta part, s'utilitza el robot Girona 500 amb un sonar multifeix muntat a un dispositiu de panoràmica i inclinació, i una càmera submarina. En aquesta part, l'algorisme es desenvolupa per tal de millorar-ne la seguretat i robustesa.

Finalment, aquesta tesi presenta resultats experimentals obtinguts amb els robots Sparus II i Girona 500. L'algorisme s'ha provat en diferents escenaris situats a St. Feliu de Guíxols: l'escullera de blocs de formigó, l'illot de la Punta del Molar i el turó submarí de l'Amarrador. Els resultats obtinguts mostren que l'algorisme presentat en aquesta tesi és capaç de guiar el robot per tal d'explorar un entorn totalment desconegut i obtenir un mapa de relleu al mateix temps que imatges. A partir de les imatges obtingudes durant els experiments d'exploració, ha sigut possible crear reconstruccions 3D dels entorns explorats.

Resumen

Los robots autónomos submarinos se utilizan actualmente en muchas aplicaciones diferentes, como por ejemplo en mapeo de proximidad, manipulación o inspección. La mayoría de veces, estas tareas se planifican con anterioridad utilizando información previa del entorno donde el robot operará. Cuando esta información previa no existe, se pueden utilizar algoritmos de exploración robótica para que el robot descubra por sus propios medios el entorno de forma segura. Los algoritmos de exploración actuales presentan limitaciones importantes, sobretodo en entornos que pueden presentar mucho relieve, donde el robot se puede encontrar con obstáculos. Además, la mayoría de algoritmos de exploración están diseñados para obtener un mapa completo del entorno con un solo tipo de datos, que normalmente son datos con el relieve o la forma del entorno. Si también se quieren obtener imágenes del entorno, con estos algoritmos es necesario realizar una segunda intervención para que el robot las obtenga a partir del mapa creado inicialmente. Combinar estas dos intervenciones en una sola permitiría ahorrar tiempo y, consecuentemente, reducir costes.

El objetivo de esta tesis es, pues, desarrollar un algoritmo de exploración robótica para vehículos submarinos autónomos que sea capaz de explorar de forma segura entornos desconocidos en 3D, obteniendo simultáneamente un mapa de rejilla con el relieve o la forma del entorno e imágenes obtenidas a poca distancia que cubran las superficies detectadas.

El algoritmo de exploración presentado funciona de forma iterativa. A partir de los datos que los sensores van percibiendo, el algoritmo genera un mapa e identifica, de forma automática, las regiones que se deben explorar a continuación. De todas las posibles regiones a explorar, el algoritmo escoge la mejor y genera un punto de vista que permitirá obtener información de la región de interés. Con tal que el robot alcance el punto de vista seleccionado, el algoritmo calcula un camino seguro desde la posición actual del robot, teniendo en cuenta los obstáculos presentes en el mapa.

La primera parte de esta tesis desarrolla un método de exploración 2D para entornos que presentan relieve. Los datos del entorno se obtienen mediante un sonar perfilador y una cámara submarina, montados en el robot Sparus II, un robot con forma de torpedo. Esta parte de la tesis continúa con el desarrollo de una versión mejorada del algoritmo de exploración, donde se propone una estrategia de filtrado de ruido para eliminar el ruido presente en el sonar, ya que afecta negativamente la consistencia de los mapas generados, y esto puede provocar que el algoritmo de exploración tome decisiones poco óptimas. Esta parte también desarrolla las estrategias necesarias para conseguir que el algoritmo se pueda implementar de forma que su ejecución sea suficientemente rápida. La segunda parte de esta tesis desarrolla un planificador de trayectorias para mejorar las capacidades

de planificación del algoritmo de exploración. El planificador de trayectorias propuesto tiene en cuenta la dinámica no lineal del vehículo y las corrientes de agua, y permite utilizar toda la gama de maniobras que el robot ofrece. La tercera parte de la tesis desarrolla un método de exploración 3D. En esta parte, se utiliza el robot Girona 500 con un sonar multihaz montado en un dispositivo de panorámica e inclinación, y una cámara submarina. En esta parte, se desarrolla el algoritmo con el fin de mejorar su seguridad y robustez.

Finalmente, esta tesis presenta resultados experimentales obtenidos con los robots Sparus II y Girona 500. El algoritmo se ha probado en diferentes escenarios situados en St. Feliu de Guíxols: la escollera de bloques de hormigón, el islote de la Punta del Molar y el monte submarino del Amarrador. Los resultados obtenidos muestran que el algoritmo presentado en esta tesis es capaz de guiar el robot para explorar un entorno totalmente desconocido y obtener un mapa de relieve al mismo tiempo que imágenes. A partir de las imágenes obtenidas durante los experimentos de exploración, ha sido posible crear reconstrucciones 3D de los entornos explorados.

1

Introduction

This chapter presents the motivation behind this Ph.D. thesis in Section 1.1, where the reader is introduced to the underwater robotic exploration problem. Then, Section 1.2 describes the context in which this work has been developed. Finally, the main objectives of this work are presented in Section 1.3, and Section 1.4 concludes with a summary of the organization of this document.

1.1 Motivation

Autonomous underwater vehicles (AUVs) have become a powerful tool to perform many underwater tasks. They are used in a wide range of applications, such as inspection of structures, bathymetric mapping or intervention. The use of AUVs presents several advantages over the use of alternative technologies such as remotely operated vehicles (ROVs). The lack of umbilical cable enables the use of AUVs in situations where an ROV could get entangled. However, developing algorithms to fully automate underwater tasks is challenging. Furthermore, underwater sensors are noisy, so the current sensor technology also imposes extra challenges not found in other domains.

When operating AUVs, usually the task to be performed is carefully planned by scientists, and then the high level commands of the mission are translated to robot commands by skilled technicians. In many applications, prior knowledge of the environment is required to plan the mission so that collisions and other safety hazards are avoided. In this context, the robot usually performs a constant altitude or a constant depth mission, keeping a safe distance from the obstacles in the scene. For applications where the robot needs to get closer to the environment, ROVs are still preferred over AUVs, as an operator can guide the robot and take decisions during the mission.

One of the applications where the robot cannot rely on prior information and has to navigate close to the obstacles in the environment is underwater exploration. Underwater exploration can be defined as the task of creating a map of a particular unknown area of the ocean, typically delimited by a bounding box. In robotic exploration, the robot starts scanning the environment and deciding where to go next to continue the exploration. Robotic exploration methods and coverage path planning (CPP) methods usually share the same goal. Coverage path planning can be defined as the task of determining a path that guarantees full sensor coverage of an area or volume of interest while avoiding obstacles. However, while coverage path planning methods often use a prior map to plan the path, exploration methods do not.

This work develops a 2-dimensional (2D) and 3-dimensional (3D) robotic exploration algorithm for autonomous underwater exploration. The goal is to have an algorithm that is able to autonomously guide an AUV so that it explores a user defined area of the ocean. As a design decision, we impose that the exploration must not rely on prior knowledge about the shape of the environment. The inspection is done in close proximity to the environment so that the resolution of the generated map and images is higher.

The exploration problem has been studied in other domains, such as terrestrial and aerial domains. It has also a lot in common with many object reconstruction algorithms, which seek to autonomously build a 3D representation of the shape of an object, usually placed in a controlled working area. All those algorithms are based on the following ideas:

- *Frontier-based (FB) exploration.* Frontier-based methods use the boundaries between different regions in the map to select the target locations to continue the exploration. Essentially, most frontier-based methods drive the robot towards the frontier between empty and unknown regions. By doing so, the robot is pushed towards the limit of what it is known and what remains unexplored. This idea was first proposed by Yamauchi [21], and has been used by many authors over the years. However, most frontier-based methods do not account for the sensor field of view (FOV).

- *View planning (VP).* View planning algorithms are based on planning a set of viewpoints from which data is captured to create a full model of the scene. A viewpoint is commonly defined as the set containing the robot position and orientation, the relative position and orientation of the sensing device, and the sensing device configuration. When performing CPP the best route that explores all viewpoints is typically found by solving a variant of the art gallery problem (AGP) and the traveling salesman problem (TSP). In contrast, robotic exploration algorithms based on VP usually use the next-best-view (NBV) approach, where the next best viewpoint is planned at each algorithm iteration according to the current map and robot location. The first example of VP using the NBV approach was developed by Connolly [22]. One of the advantages of VP algorithms is that they explicitly account for the sensor FOV. However, most VP algorithms are not able to evaluate all possible viewpoints due to time or computational constraints, so they make some assumptions regarding where the viewpoints are located.

- *Reactive algorithms (RAs).* Reactive and control-based algorithms have been used in robotic exploration [23]. Even potential fields can be used to perform robotic exploration [24]. They provide a simple and easy to implement framework but often suffer from local minima problems. With them, it is also difficult to precisely account for the sensor FOV.
- *Deep learning (DL).* Recently, some authors have proposed the use of DL to improve the performance of robotic exploration algorithms [25]. For instance, DL can be used to predict the shape of the unknown regions of the environment to improve the exploration strategy.

Many of the previous ideas are combined in the literature with information-theoretic approaches, which are usually built upon the Bayesian statistical framework, and choose the next best viewpoint according to the information gain. The information gain is usually evaluated by considering the entropy reduction in the map achieved by the exploration of the viewpoints. Some examples of information-theoretic approaches can be found in [26], [27], [28] and [29].

A complete and updated review of the state of the art in robotic exploration work can be found in the fifth publication of this compendium, in Chapter 6.

The overall idea behind the algorithm developed during this thesis is to combine FB methods with VP so that viewpoints are generated to cover the frontiers in the map. The environment is represented using a grid map, in which the space is encoded as a multidimensional array of cells, whose size depend on the chosen resolution. Each cell in the map is given the *Unknown* initial label, and then the state of the cells in the map is updated during the mission according to the measurements obtained from the environment. Throughout the publications presented in this thesis there is an evolution and refinement of the chosen cells and how they are updated, which reflects the knowledge that the authors have gathered during the development and testing of the algorithm.

An important aspect of the algorithm developed throughout this thesis is that it ensures not only coverage with a range sensor, providing an occupancy map, but it also ensures that images are captured from all the detected surfaces in the scene in a single exploration mission. Therefore, our approach is very different from the typical approach where the robot performs an exploration mission and returns to the surface with enough data to create an occupancy map from the environment and then, if images are required, a second mission is necessary to gather optical data from the scene. Doing the optical inspection in a second mission is more time consuming and more expensive, and it is difficult to precisely revisit interesting locations due to the localization drift. Because of that, our approach of conducting exploration while simultaneously taking into account range and visual measurements brings in a significant advantage.

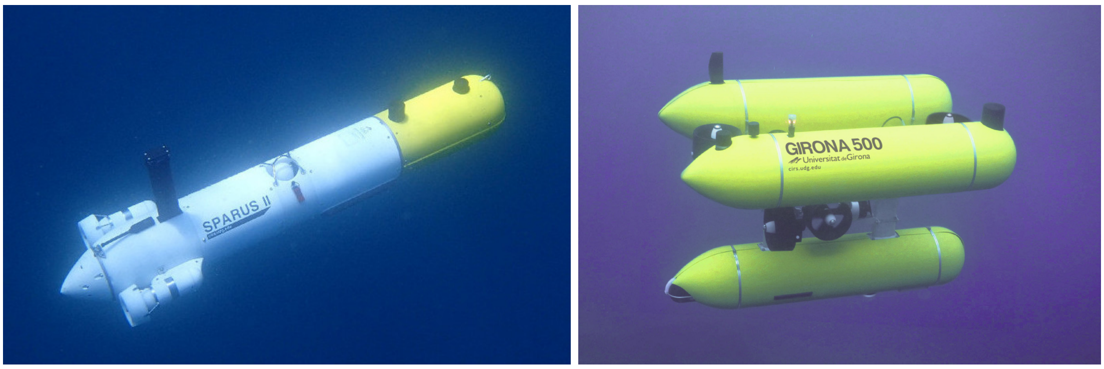
To improve the path planning capabilities within the exploration framework, this thesis has also worked on the start to goal motion planning problem. In the context of exploration, start to goal planning is required to compute safe paths that enable the vehicle to reach the desired viewpoints generated by the exploration algorithm. The proposed algorithm is able to compute a safe trajectory which accounts for the dynamic constraints of the vehicle and also the water currents. At the same time, the computational time is kept low, which enables the use of the proposed planner in online applications.

Since the algorithm developed in this work has to run inside the robot's onboard computer, a lot of attention has been put to the computational efficiency of each operation performed. In this regard, the exploration algorithm has been designed so that it takes advantage of the nearest neighbor operations made possible by a tree-based data structure.

1.2 Context

The work presented in this thesis has been supported by FPU14/05493 grant from the Spanish Government and has been developed in the underwater robotics research center (CIRS), which is part of the VICOROB institute from the Universitat de Girona (UdG). The group started its activity in underwater vision and robotics in 1992. It is a leading team in the underwater research community, and it is currently formed by predoctoral and postdoctoral researchers, engineers, technicians and permanent staff. It has participated in many National and European projects and actively participates in technology transfer projects.

Over the years, the group has developed several AUVs. Currently, two robots are operational and available as research platforms: the Sparus II AUV [1] and the Girona 500 AUV [30] (see Figure 1.1). Both have been used in the context of this thesis. The group also has a research vessel, from where the robots can be deployed and recovered using a crane during the sea trials (see Figure 1.2).



(a) (b)

Figure 1.1: Robots currently operational at CIRS. (a) Sparus II AUV, a torpedo shaped vehicle with partial hovering capabilities. (b) Girona 500 AUV, a bigger platform with more payload area than Sparus II, with full hovering capabilities.

(a) (b)

Figure 1.2: The *Sextant* research vessel. (a) Shows an overall view of the 7 meters long vessel. (b) A crane is used to deploy and recover the robots.

The experiments, equipment and infrastructure resources used in this thesis have been partially funded by the following projects:

- MINECO Project ARCHROV (part of MERBOTS) (ref. DPI2014-57746-C3-3-R) funded by the Spanish Ministry of Science and Innovation.
- EU H2020 Project EXCELLABUST (ref. H2020-TWINN-2015(CSA)-691980) funded by the European Commission.
- EU H2020 Project STRONGMAR (ref. H2020-TWINN-2015(CSA)-692427) funded by the European Commission.
- MINECO Project 3DAUV (ref. DPI2015-73978-JIN) funded by the Spanish Ministry of Science and Innovation.
- MINECO Project GIRONA1000 (ref. DPI2017-86372-C3-2-R) funded by the Spanish Ministry of Science and Innovation.

1.3 Objectives

With the motivations of this thesis described, we can now state what the main goal is.

> ***The goal of this thesis is to develop a robotic exploration framework for autonomous underwater vehicles that is capable of exploring unknown environments in 2D and 3D, obtaining simultaneously a map with the relief or shape of the environment and images at a close distance. At the same time, the planned movements of the vehicle should respect the dynamic restrictions imposed by the robot being used.***

This general goal can be divided into the following objectives:

- Survey the state of the art in the robotic exploration field to understand the work and lines of research of other authors in the field.

- Design a 2D exploration algorithm that is able to map an unexplored environment with a sonar sensor and with cameras in a single autonomous mission.
- Extend the 2D algorithm to perform 3D exploration, considering also the occupancy data from the sonar sensor and the optical data from the cameras in a single exploration mission.
- Improve the motion planning capabilities of the exploration algorithm by developing a start to goal online planning solution that accounts for the dynamics of a typical underwater robot.
- Validate the framework experimentally and extensively, both in simulation and in multiple field trials carried out in representative environments using real robot platforms and sensors.

The survey of the state of the art and the validation of the framework objectives have been an on-going effort throughout the development of the thesis, and as such they are reflected in all the publications of this compendium. Every publication contains a state of the art review, and also experimental evaluation of the proposal. The basic 2D exploration algorithm, the improved 2D algorithm and the motion planning goals have been covered in dedicated publications, using the Sparus II AUV as the experimental platform. The 3D exploration algorithm has also been covered in a dedicated publication, using the Girona 500 AUV.

1.4 Document structure

This document is structured in the following chapters:

- **Chapter 2:** This chapter presents, through the publication *Sparus II AUV-A Hovering Vehicle for Seabed Inspection*, an introduction to the work developed in this thesis. Preliminary results are shown, and the work is presented as one of the main research lines in the CIRS lab. This line of research is presented as an extension of the start to goal planning topic, and proposed as a solution to perform autonomous underwater tasks, such as online mapping, inspection and exploration.
- **Chapter 3:** This chapter presents the first version of the proposed algorithm through the publication *Online View Planning for Inspecting Unexplored Underwater Structures*. In this publication, a detailed description of the overall approach is presented, where each part of the algorithm is discussed: the world representation, the map generation, the viewpoint generation, the path generation and the vehicle control. Experimental results in 2D using the Sparus II AUV are reported in the harbor and in the breakwater blocks scenarios.
- **Chapter 4:** This chapter presents several improvements to the 2D algorithm through the publication *2D Frontier-based Viewpoint Generation for Exploring and Mapping Underwater Environments*. This publication describes the improved 2D algorithm in detail, and presents experimental data in challenging scenarios, such as the breakwater blocks, Punta del Molar and the Amarrador underwater boulder, demonstrating the robustness of the 2D algorithm.

- **Chapter 5:** In the publication of this chapter, entitled *Online Multilayered Motion Planning with Dynamic Constraints for Autonomous Underwater Vehicles*, a start to goal motion planner for autonomous underwater vehicles is presented to improve the planning capabilities within the exploration algorithm. The proposed motion planner accounts for the vehicle dynamics and generates feasible paths while accounting for water currents. Its efficiency enables its use in online planning.
- **Chapter 6:** The publication of this chapter, entitled *Multisensor Online 3D View Planning for Autonomous Underwater Exploration*, presents the last version of the 3D exploration algorithm and the obtained experimental results using the Girona 500 AUV. This publication presents the most challenging experiments carried out in the context of this thesis, which consist in autonomously mapping an underwater boulder, obtaining an occupancy map and optical data in a single mission. It also presents a complete state of the art review of other robotic exploration publications.
- **Chapter 7:** This chapter presents a summary of the results obtained in the context of this thesis.
- **Chapter 8:** Finally, the last chapter presents the conclusions and some guidelines for future work.

2

Sparus II AUV - A Hovering Vehicle for Seabed Inspection

In this chapter, we propose the use of Sparus II AUV for seabed inspection, view planning and robotic exploration. This publication presents a basic version of the work developed in this thesis in the context of the work developed in the lab, and showcases different applications for the proposed algorithm. The work of this thesis is presented as an extension of the start to goal motion planning line, developed previously in the lab.

Title: Sparus II AUV-A Hovering Vehicle for Seabed Inspection
Authors: Marc Carreras, Juan David Hernández, **Eduard Vidal**, Narcís Palomeras, David Ribas, and Pere Ridao
Journal: IEEE Journal of Oceanic Engineering (JOE)
Volume: 43, Number: 2, Pages: 344–355, Published: 2018
Quality index: JCR2017 Oceanography, Impact Factor: 2.065, Q2

Marc Carreras, Juan David Hernández, Eduard Vidal, Narcís Palomeras, David Ribas, and Pere Ridao. "Sparus II AUV-A Hovering Vehicle for Seabed Inspection". *IEEE Journal of Oceanic Engineering*. Vol. 43, Issue 2 (2018) : 344–355.

https://doi.org/10.1109/JOE.2018.2792278

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Abstract

This paper proposes the use of path-planning algorithms for hovering autonomous underwater vehicles (AUVs) in applications where the robot needs to adapt online its trajectory for inspection or safety purposes. In particular, it proposes the platform Sparus II AUV and a set of planning algorithms to conduct these new AUV capabilities. These algorithms generate trajectories under motion constraints, which can be followed without deviations, to ensure the safety even when passing close to obstacles. View planning algorithms are also combined to decide the movements to be executed to discover the unexplored seabed or target, and to cover it with a camera or sonar. Online mapping with profiling sonars and online planning with fast sampling-based algorithms allow the execution of missions without any previous knowledge of the 3-D shape of the environment. Real 2-D results in an artificial harbor structure and simulated natural rocky canyon demonstrate the feasibility of the approach for avoiding or inspecting the underwater environment. These new AUV capabilities can be used to acquire images of the environment that can be used to inspect and map the habitat.

Keywords

Autonomous underwater vehicle (AUV), hovering AUV, online path planning and view planning (VP).

3

Online View Planning for Inspecting Unexplored Underwater Structures

In this chapter, we present the first version of the 2D exploration algorithm. The algorithm presented in this work uses a scanning profiling sonar and a set of cameras. Details of the overall approach are given, and results are also shown using the Sparus II AUV. A 3D reconstruction of the explored scene is also provided.

Title: Online View Planning for Inspecting Unexplored Underwater Structures
Authors: **Eduard Vidal**, Juan David Hernández, Klemen Istenič, and Marc Carreras
Journal: IEEE Robotics and Automation Letters (RA-L)
Volume: 99, Number: 3, Pages: 1436–1443, Published: 2017
Quality index: Not indexed yet

Eduard Vidal, Juan David Hernández, Klemen Istenic, and Marc Carreras. “Online View Planning for Inspecting Unexplored Underwater Structures”. IEEE Robotics and Automation Letters. Vol. 99, Issue 3 (2017) : 1436–1443.

https://doi.org/10.1109/LRA.2017.2671415

Manuscript received September 10, 2016; accepted February 2, 2017. Date of publication February 17, 2017

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Abstract

In this letter, we propose a method to automate the exploration of unknown underwater structures for autonomous underwater vehicles (AUVs). The proposed algorithm iteratively incorporates exteroceptive sensor data and replans the next-best-view in order to fully map an underwater structure. This approach does not require prior environment information. However, a safe exploration depth and the exploration area (defined by a bounding box, parameterized by its size, location, and resolution) must be provided by the user. The algorithm operates online by iteratively conducting the following three tasks: (1) Profiling sonar data are first incorporated into a 2-D grid map, where voxels are labeled according to their state (a voxel can be labeled as empty, unseen, occluded, occplane, occupied, or viewed). (2) Useful viewpoints to continue exploration are generated according to the map. (3) A safe path is generated to guide the robot toward the next viewpoint location. Two sensors are used in this approach: a scanning profiling sonar, which is used to build an occupancy map of the surroundings, and an optical camera, which acquires optical data of the scene. Finally, in order to demonstrate the feasibility of our approach, we provide real-world results using the Sparus II AUV.

Keywords

Autonomous vehicle navigation, marine robotics, motion and path planning.

4

2D Frontier-based Viewpoint Generation for Exploring and Mapping Underwater Environments

In this chapter, we present the improved version of the 2D exploration algorithm developed in this thesis. This publication describes the algorithm with the improvements, and also presents extensive experimental data using the Sparus II AUV in the Amarrador seamount. The robot was equipped with a scanning profiling sonar and a set of cameras, and a 3D reconstruction of the seamount is presented.

Title: Two-Dimensional frontier-based viewpoint generation for exploring and mapping underwater environments
Authors: **Eduard Vidal**, Narcís Palomeras, Klemen Istenič, Juan David Hernández, and Marc Carreras
Journal: Sensors (Switzerland)
Volume: 19, Number: 6, Pages: 1460, Published: 2019
Quality index: JCR2017 Instruments & Instrumentation, Impact Factor: 2.475, Q2

sensors

MDPI

Article

Two-Dimensional Frontier-Based Viewpoint Generation for Exploring and Mapping Underwater Environments

Eduard Vidal [1,*], Narcís Palomeras [1], Klemen Istenič [1] and Juan David Hernández [2] and Marc Carreras [1]

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Abstract: To autonomously explore complex underwater environments, it is convenient to develop motion planning strategies that do not depend on prior information. In this publication, we present a robotic exploration algorithm for autonomous underwater vehicles (AUVs) that is able to guide the robot so that it explores an unknown 2-dimensional (2D) environment. The algorithm is built upon view planning (VP) and frontier-based (FB) strategies. Traditional robotic exploration algorithms seek full coverage of the scene with data from only one sensor. If data coverage is required for multiple sensors, multiple exploration missions are required. Our approach has been designed to sense the environment achieving full coverage with data from two sensors in a single exploration mission: occupancy data from the profiling sonar, from which the shape of the environment is perceived, and optical data from the camera, to capture the details of the environment. This saves time and mission costs. The algorithm has been designed to be computationally efficient, so that it can run online in the AUV's onboard computer. In our approach, the environment is represented using a labeled quadtree occupancy map which, at the same time, is used to generate the viewpoints that guide the exploration. We have tested the algorithm in different environments through numerous experiments, which include sea operations using the Sparus II AUV and its sensor suite.

Keywords: autonomous underwater vehicle (AUV); robotic exploration; view planning (VP); motion planning; frontier-based (FB) exploration; next-best-view (NBV)

1. Introduction

Autonomous underwater vehicles (AUVs) have become a fundamental tool to perform many underwater tasks, such as close inspection of structures [1], near-bottom surveys [2], or intervention [3]. The use of AUVs has many advantages over alternative technologies such as remotely operated vehicles (ROVs). For instance, the lack of an umbilical cable increases the freedom of movement of AUVs, allowing missions to take place in complex scenarios with high relief or complex artificial structures, where the umbilical cable could get entangled. Furthermore, AUVs require less human intervention allowing for potentially cheaper sea operations. Providing AUVs with the ability to carry out tasks autonomously is a challenge. When the target is in areas with a high level of relief, current algorithms have significant limitations. Our proposal focuses on enabling the use of AUVs in these challenging cases for inspection and mapping purposes.

In this work, we present an algorithm which is capable of guiding an underwater robot to obtain a map of a region of interest. Traditionally, this problem has been studied in two different research fields:

coverage path planning (CPP) algorithms are focused on obtaining a trajectory that passes through all regions of an area or volume of interest, using a map which can sometimes be of low accuracy. Robotic exploration algorithms, on the other hand, are designed so that there is no need for a prior map, with the goal of obtaining a map of a completely unknown environment.

In most cases, the available information about a particular region of the sea is scarce. Because of that, we have designed our algorithm so that it does not use a prior map of the area of interest. The proposed algorithm is therefore an underwater robotic exploration algorithm. As a consequence, the implementation of the algorithm has to be able to run in the robot's computer, with limited processing power, in order to guide the robot as the mission progresses. To meet this requirement, our algorithm has been designed with computational efficiency in mind, selecting the best data structures to represent the data so that the operations required by the exploration algorithm can be performed fast enough for online planning.

Most robotic exploration algorithms are based on the following ideas:

- *Frontier-based (FB) exploration*. Frontier-based methods guide the exploration by focusing on the regions between known an unknown space. This idea was first proposed by Yamauchi [4]. The exploration is guided according to interesting regions in the map. However, the sensor field of view (FOV) is usually not taken explicitly into account. Furthermore, if the target frontier is the boundary between known and unknown space, as done in the original and many other publications, the robot has a tendency to navigate in a straight line exploring as much as possible until something is reached. This behavior is desirable for indoor exploration, but it is not appropriate for underwater exploration because the robot will only explore open water unless some limits are specified.
- *View planning (VP)*. View planning algorithms evaluate different candidate viewpoints to determine the actions that the robot must perform. A viewpoint is commonly defined as a particular configuration of robot/sensors. When performing CPP the best route that explores all viewpoints is commonly found by solving a variant of the art gallery problem (AGP) and the traveling salesman problem (TSP). In contrast, robotic exploration algorithms based on VP usually use the next-best-view (NBV) approach, where the next best viewpoint is planned online according to the current map and robot location. The first example of VP using the NBV approach was developed by Connolly [5]. One of the advantages of VP algorithms is that they are explicitly aware of the sensor FOV. However, since usually there is an infinite amount of possible viewpoints it is difficult to select them for their evaluation. For this reason, it is common to generate the viewpoints randomly or to reduce the amount of possible viewpoints according to the specific problem. Furthermore, to properly evaluate a viewpoint it is sometimes necessary to use a ray-casting approach, which might be too slow for online computation.
- *Reactive algorithms (RAs)*. Reactive algorithms, such as control-based approaches, can also be used for robotic exploration as done in McEwen et al. [6]. Even potential fields can be used for robotic exploration [7]. They provide a simple framework which is easy to implement, but they suffer from local minima problems, and it is difficult to precisely account for the FOV of the sensors during planning.

The proposed approach combines the strengths of FB exploration and VP methods to obtain an algorithm specifically tailored for underwater robotic exploration. The frontiers extracted from the map are used to deterministically generate viewpoints for exploration. By considering frontiers between explored and unexplored areas, and between seen and unseen areas, data continuity and overlap is imposed, which is good for mapping purposes because it enables feature-matching and data registration between scans. A requirement of our proposed method is that the explored structure must have vertical relief. Then, the exploration is performed in a 2D slice at a user defined depth. Furthermore, our algorithm is capable of autonomously guiding an underwater robot to obtain both the occupancy map and the optical data of a region of interest in a single exploration mission.

To demonstrate the feasibility of our approach we present simulations and experimental data using the Sparus II AUV. The proposed approach is an extension of our previous work in [8,9]. In this work, several aspects of the viewpoint generation process have been improved, mainly to improve robustness and safety. New experimental data has been obtained in challenging scenarios, and a quantitative evaluation of the obtained results is presented.

The remainder of this paper is organized as follows. Section 2 presents a review of important related work to our underwater robotic exploration problem. Then, Section 3 explains the details of the proposed underwater robotic exploration algorithm. Section 4 shows the robotic platform that has been used to generate the experimental outcomes, presented in Section 5. Finally, Section 6 presents the conclusions and evaluates further lines of investigation.

2. Related Work

This section presents important related work to our underwater robotic exploration problem. Table 1 summarizes this section presenting a classification of algorithms by the amount of *prior knowledge* used, *domain*, *dimensionality* and *approach*.

Table 1. Summary of the state of the art. The algorithms are classified by the amount of *prior knowledge* used, *domain*, *dimensionality* and *approach*.

Category	Domain	Space	Reference	Approach	Remarks
With prior map	Underwater	2.5D	Galceran et al. [10]	CPP and horizontal profiles	The terrain is classified in regions of low and high relief. The offline mission is adapted online using stochastic trajectory optimization
		3D	Palomeras et al. [11]	VP	A minimum set of views and TSP is used togenerate exploration trajectory, followed using SLAM. Simulation only
	Terrestrial	2D/3D	Blaer and Allen [12]	VP	Two stages. First, minimum set of views and TSP in 2D. Then, NBV in 3D
	Aerial	3D	Bircher et al. [13]	VP	Iterative viewpoint resampling with TSP in 3D
Without prior map	Underwater	2D	Williams et al. [14]	VP	Automatic target reinspection after an initial constant altitude mission
			Vidal et al. [8], Vidal et al. [9]	VP	Our previous work. Views are planned according to several frontiers
		3D	Kim and Eustice [15], Hover et al. [1]	VP	Perception driven navigation for the ship's hull without prior map. Minimum set of views and TSP using a prior map for the propellers
			McEwen et al. [6]	RA	The 3D map is obtained by performing wall following at different depths
	Object reconstruction	3D	Connolly [5]	VP	Original proposal of the next-best-view (NBV) approach
			Vasquez-Gomez et al. [16], Vasquez-Gomez et al. [17]	FB and VP	It uses the frontiers to plan the NBV. Uncertainty is taken into account. Position and maximum size of the object must be known
			Isler et al. [18]	FB and VP	Information gain is used to plan the NBV. Position and maximum size of the object must be known
	Terrestrial	2D	Yamauchi [4]	FB	Original proposal of the FB approach. It clusters the frontier cells
			González-Baños and Mao [19]	VP	It builds a polygonal model of the environment and plans the NBV using a randomized algorithm that maximizes the information gain
			Burgard et al. [20]	FB	Multirobot exploration. Each robot is equipped with a 360 degree range sensor
			Fox et al. [21]	FB and VP	Multirobot exploration. Shared maps. The robots actively seek to verify their relative locations
			Stachniss et al. [22]	FB	Multirobot exploration. A classifier assigns labels to different locations in the map, and these labels are used in the utility function that guides the exploration
			Renzaglia and Martinelli [7]	RA	Potential fields are used to guide the exploration of a team of robots
	Aerial	3D	Schmid et al. [23]	VP	Viewpoints are planned using a coarse digital surface (DSM) in 2.5D. The data acquired from the viewpoints is used to create a 3D reconstruction
			Yoder and Scherer [24]	FB and VP	The exploration utility function is based on the visibility of 2D frontiers on the 2D surface of a 3D object
			Bircher et al. [25], Papachristos et al. [26]	Random tree and VP	A random tree is generated where the nodes are evaluated according to the amount of unmapped space that it explores

2.1. Methods That Use a Prior Map

In the underwater domain, Galceran et al. [10] presented a 2.5D approach for inspection of complex underwater structures. In their approach, a prior map is used to compute a nominal path that covers all the scene. Then, the robot follows the precomputed path while adapting it to what is perceived in situ, thus allowing some deviation to account for the navigation drift and inaccuracies in the prior map. Recently, Palomeras et al. [11] presented a VP algorithm which samples viewpoints from a previous model and then solves the TSP. In their work, simultaneous localization and mapping (SLAM) is used during the mission to ensure minimal deviations with respect to the previously planned trajectory. However, results were supported by simulations only.

Regarding other domains, Blaer and Allen [12] presented a two stage VP approach for 3-dimensional (3D) site modeling with unmanned ground vehicles (UGVs). In their initial stage, a minimal set of views is planned in 2D to cover a prior map of the scene, and then, in a second stage, the resulting model is improved by considering 3D views of the 3D model obtained in the first stage. Bircher et al. [13] presented a VP algorithm for structural inspection using unmanned aerial vehicles (UAVs). Their method employs an alternating two-step optimization to find viewpoints for coverage while reducing the path cost.

All the aforementioned methods can be used when a prior map is available. Although they share some similarities with the methods in the following section, they are not directly applicable to our problem since we do not have a prior map of the area to be explored.

2.2. Methods That Do Not Use a Prior Map

In the underwater domain, the robotic exploration literature is scarce. Aside from our previous VP work in Vidal et al. [8] and Vidal et al. [9], Williams et al. [14] proposed a target reinspection method for AUVs equipped with a synthetic aperture sonar (SAS). In their approach, after a first constant altitude mission, locations of potential interest are automatically inspected before the vehicle surfaces, which can be considered a form of VP exploration. However, the initial constant altitude mission can only be performed if the area does not contain 3D relief, so it is not suitable to our exploration problem. Regarding 3D environments, Kim and Eustice [15] and Hover et al. [1] developed VP techniques for ship hull inspection. While a prior rough map was necessary to plan the path to explore the propellers and rudders, the rest of the hull was inspected without a prior model. The inspection follows a preplanned lawn-mover trajectory that is merged with target revisiting. This approach is very specific and it is not directly applicable to our exploration problem. McEwen et al. [6] presented a reactive and control-based approach where an iceberg was mapped by performing several autonomous wall following missions at different depths. This approach can not be directly applied to our problem because we can have multiple objects with high relief (for instance, our breakwater blocks scenario).

Some of the methods that are used for object reconstruction can also be adapted for robotic exploration. Connolly [5] proposed the NBV methodology to autonomously plan views to reconstruct a 3D object. In the same line, Vasquez-Gomez et al. [16] presented a NBV algorithm to model arbitrary objects in 3D, and Vasquez-Gomez et al. [17] refined the method by adding uncertainties. Their method does not need prior knowledge regarding the shape of the object, but information about its size and location is required. Isler et al. [18] also developed a NBV uncertainty-aware approach for active volumetric 3D reconstruction. Although the aforementioned 3D reconstruction methods cannot be directly applied to underwater exploration, our algorithm is based on ideas developed in these methods, such as the NBV methodology, so they are relevant to our work.

Regarding exploration algorithms for ground vehicles, Yamauchi [4] initially proposed the FB method for 2D robotic exploration. González- Baños and Mao [19] applied NBV strategies to robotic exploration by planning randomized views that maximize information gain over a polygonal model of the environment. Burgard et al. [20] explored FB methods and even extended them to work with multiple robots. Then, Fox et al. [21] proposed a distributed multirobot exploration algorithm for ground vehicles where the robots actively verify their relative locations with the goal of improving the map consistency. Finally, Stachniss et al. [22] proposed the exploration of unknown indoor environments using a team of mobile robots. Their method uses a classifier to assign labels to different locations in the map, and then these labels are used to guide the exploration using a utility function.

In the aerial domain, Schmid et al. [23] presented a two step process where first a coarse digital surface (DSM) of the environment is built, and then viewpoints are planned to acquire the data for a 3D reconstruction. Yoder and Scherer [24] presented a FB algorithm for micro aerial vehicles (MAVs). In their approach, the different viewpoints are evaluated according to the visibility of frontier cells, determined by ray-tracing. Finally, Bircher et al. [25] and Papachristos et al. [26] proposed a method based on the rapidly-exploring random tree (RRT) to perform exploration without a prior map. A random tree is generated and the best branch is chosen according to the information gain, measured by the amount of mapped and unmapped cells visited when following the generated viewpoints in the branch.

Our algorithm combines different aspects from the presented related work. Furthermore, we extend existing approaches by considering coverage of two sensors simultaneously in a single exploration mission. To the best of the authors knowledge, this is the first underwater exploration algorithm that has this capability.

3. Frontier-Based Viewpoint Generation Method for Exploration

The proposed 2D robotic exploration method seeks full coverage of the environment with two different types of data:

- Occupancy data: a mechanically scanning profiling sonar is used to obtain occupancy data from the environment. This kind of sonar sensors mechanically rotate a narrow acoustic beam in order to measure ranges from different orientations. Since the beam rotates along one axis, the field of view covers a user defined sector from a plane. A scan usually takes several seconds to be obtained.
- Optical data: a camera acquires images from the environment. The exploration algorithm does not use the images so no live feedback from the camera is required. Only an estimation of its FOV is used for exploration planning purposes.

The algorithm has been designed to fit a hierarchical/deliberative robotic paradigm where, according to Arkin [27], the tasks that the robot iteratively performs can be classified in three categories: *sense*, *plan* and *act* (see Figure 1).

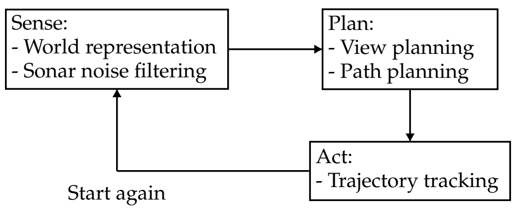


Figure 1. Each part of the proposed algorithm is associated to the corresponding task in the hierarchical/deliberative robotic paradigm.

In the remainder of this section the different parts of the proposed method will be described.

3.1. World Representation (Sense)

Using the data received from the sonar sensor, and considering the FOV of the camera, our approach creates a labeled grid map to represent and encode the information perceived from the environment. The different possible cell labels are:

- Unknown cells. The environment is initially assumed to be unknown. Thus, this is the initial state label for all cells in the map.

- Empty cells. They represent collision-free areas where the vehicle can navigate.
- Occupied cells. They correspond to the areas where the profiling sonar has detected an obstacle. They represent walls and objects in the environment.
- Viewed cells. The occupied cells that have been inside the camera FOV are labeled as viewed.
- Range candidate cells. The unknown cells that are next to empty and occupied cells are range candidate cells because they represent regions of potential interest to continue the occupancy exploration.
- Camera candidate cells. The occupied cells that are next to empty and viewed cells are camera candidate cells because they represent the areas that should be optically explored.

Figure 2 depicts all labels in a single exploration capture. When new data is received from the sonar, the cell logic diagram represented in Figure 3 is followed to determine the label that each cell is given. The label of a cell can change several times during a mission. For instance, a cell that was initially given the occupied label might become empty if it receives enough empty measurements from the sonar (this behavior is represented by the *proportion thresholding* node in the diagram of Figure 3).

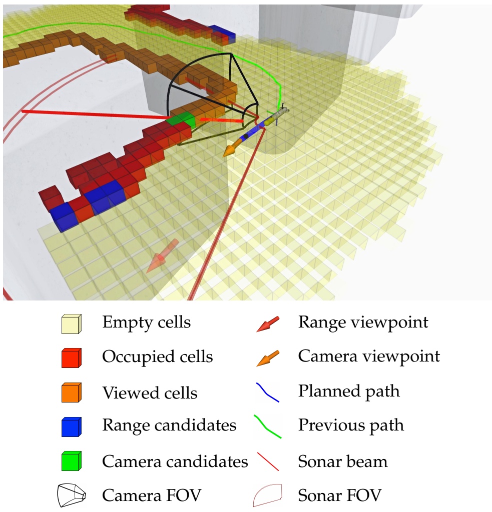


Figure 2. This figure shows all possible cell labels in a single exploration picture. The FOVs of the sensors are also shown.

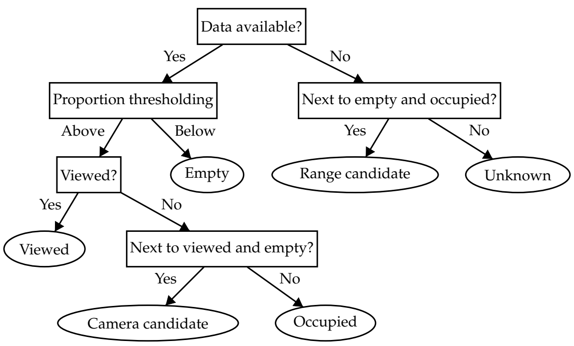


Figure 3. Map generation algorithm. After following the algorithm, a cell is classified and a label is obtained (leafs). When new measurements are received for a cell, the algorithm reevaluates its new label.

One of the novelties of our proposed algorithm is that the grid map is internally stored in several quadtrees. A quadtree is a space partitioning tree-based data structure which recursively subdivides each node to exactly four children (see Figure 4). This data structure enables some operations to be performed efficiently, such as:

- Nearest neighbors and k-nearest neighbors queries. For any specific target cell, it is possible to find the nearest cell or cells of a particular label.
- Range queries. For any specific target cell, it is possible to find all the cells within a certain distance for cells of a particular label.

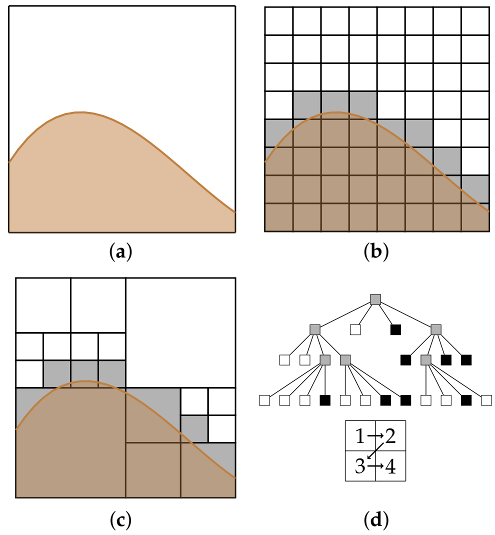


Figure 4. Example of a quadtree data structure: (**a**) the structure to represent; (**b**) a rasterized version of the structure, where the space represented using equally sized cells; (**c**) recursive subdivision of the space to represent the occupancy as a quadtree; and (**d**) the corresponding tree.

In our approach, several quadtrees are used so that the previous operations can be performed to the required cell labels in isolation, and we take advantage of this in the viewpoint generation process.

There exist public implementations of such tree data structures. For instance, the Octomap framework from Hornung et al. [28] implements an octree data structure (3D equivalent of a quadtree) and it is common in the robotic community. However, at the time of this publication, Octomap does not provide an implementation of nearest neighbor and range queries. To overcome this limitation, we have implemented our own quadtree data structure.

Finally, our map representation can be easily adapted to 3D environments by using an octree data structure instead of a quadtree. The rest of the operations, such as the computation of the surface normal and queries to the tree, are also well defined in a 3D space.

3.2. Sonar Noise Filtering (Sense)

Underwater sonar sensors suffer from different kinds of noise, which can potentially corrupt the map created from such data. Our robotic exploration algorithm relies on sonar data to determine what are the next best actions to take for exploration, so it is important to minimize the negative effects of the sonar noise.

When a sonar measurement is obtained, we first apply some basic filtering, which discards data in several situations:

- When the measurement is close to the minimum and maximum range of the sensor.
- When the measurement corresponds to a location near the water surface.
- When the vehicle is not stable or moving fast.

After basic filtering has been performed, the measurement is incorporated into the map according to the strategy we defined in Vidal et al. [9], which improves the map consistency when false negatives are present. If the right combination of sensor measurements is received, empty space can appear behind obstacles, as depicted in Figure 5. Our approach is able to overcome this problem and generates coherent maps even when false negatives are received. The basic idea behind the false negative noise rejection algorithm is that empty measurements can only come from nearby empty cells, so when a cell changes its state from empty to a different state, neighboring empty cells must be reevaluated.

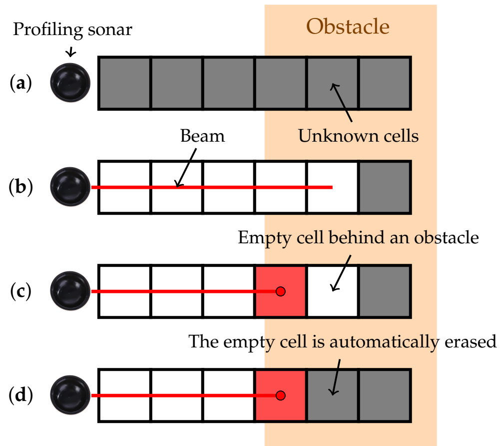


Figure 5. If not accounted for, false negatives can affect the map consistency. Consider the following sequence of events: (**a**) initially all cells have unknown state; (**b**) a false negative is received, resulting in empty cells along the beam until the maximum range of the sensor; and (**c**,**d**) finally a correct measurement is received. If each cell is considered independently, this sequence of events leaves empty cells behind the occupied cell (**c**). With our approach, this situation is detected and empty cells behind the obstacle are automatically erased (**d**) so that empty space is consistent with all occupied measurements.

3.3. View Planning (Plan)

Once the data from the sensors has been incorporated into our map, the next step is to generate viewpoints at locations that allow the exploration to continue. The proposed view planning strategy has been designed so that it takes advantage of the efficient operations allowed by our map representation. This is key to achieve the required performance to enable online missions.

Two different types of viewpoints are generated:

- *Range viewpoints.* Each range candidate cell in the map potentially generates a range viewpoint. Range viewpoints allow the exploration of the environment using the scanning profiling sonar, as they are focused on the frontier between occupied and unknown regions.
- *Camera viewpoints.* Camera candidate cells represent the frontier between optically explored and unexplored areas, and they potentially generate camera viewpoints.

Figure 6 depicts an example of the viewpoint generation process. To generate a viewpoint from a candidate cell the following deterministic procedure is followed:

- The surface normal is computed using as a reference the occupied and viewed cells around the candidate cell.

- The viewpoint is placed along the surface normal at a user defined distance, which must account for the sensor FOV.
- If the generated viewpoint is inside an empty cell it is stored for further evaluation. Otherwise, it is discarded.
- If the generated viewpoint is too close to the obstacles it is discarded. Otherwise, it is considered a safe viewpoint. Due to safety concerns, in this work, the concept of safe viewpoints is more strict than in [8,9].

The fact that the viewpoint generation process is deterministic is good for repeatability and overall understanding of the exploration maneuvers.

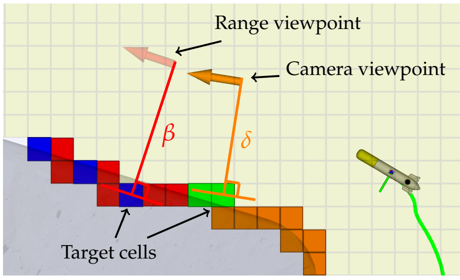


Figure 6. Viewpoint generation example. Each target cell generates a viewpoint at a user configurable distance (in this case, β and δ) along the estimated surface normal.

Once the set of all safe viewpoints has been computed, the viewpoints are evaluated according to a cost function, which captures how far a viewpoint is with respect to the current robot configuration. At this stage, both range and camera viewpoints are considered without prioritizing one over the other. Unfortunately, solving a complete path planning problem for each viewpoint is not possible online due to computational time constraints. Alternatively, the proposed cost function uses a weighted Euclidean distance which additionally accounts for the difference in orientation at the beginning and at the end of the path. While in [8,9] the weighting factor had to be manually chosen, in this work it is automatically computed using the maximum surge velocity and maximum yaw turning rate. Once all viewpoints have been evaluated, the viewpoint with the lowest cost value is selected. The cost function is described by Equations (1) and (2):

$$\beta = \mathrm{atan2}(p_y - q_y, p_x - q_x) \tag{1}$$

$$cost(q,p) = \|p_{xy} - q_{xy}\| + \frac{v_{max}}{\dot{\theta}_{max}} \left(|\mathrm{wrap}(\beta - q_\theta)| + |\mathrm{wrap}(p_\theta - \beta)|\right) \tag{2}$$

where q represents the robot configuration, p represents the viewpoint configuration, v_{max} is the maximum surge velocity, $\dot{\theta}_{max}$ is the maximum turning rate and wrap() converts an angle to a value contained within the range $(-\pi, \pi]$.

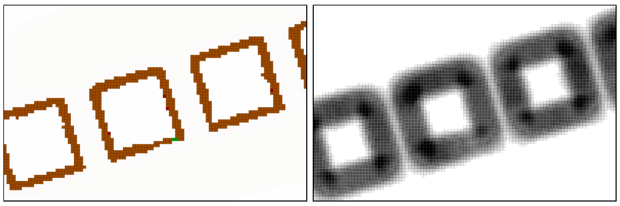
Finally, the algorithm stops the exploration when there are no more candidate viewpoints or when a timeout has expired.

3.4. Path Planning (Plan)

After computing the next best viewpoint, the robot has to navigate from its current configuration to the selected viewpoint, while avoiding the obstacles present in the current map. To generate such trajectories, we propose the use of the asymptotic optimal rapidly-exploring random tree (RRT*) path planner.

Since the robotic exploration algorithm runs on the robot's computer, with limited computational resources, we have simplified the planning problem to compute paths in a 2D configuration space, where a configuration contains only the position of the robot. Considering the orientation of the vehicle in the path planning would significantly slow down the planner, making it unsuitable for online purposes. At the same time, safety can be preserved by checking whether the smallest possible circular area containing the robot is colliding with the obstacles in the map (thus ensuring the state is valid in any possible orientation).

In our implementation, the path planner optimizes the integral of a risk function along the path. The risk associated with a particular state reflects how close it is to the obstacles in the map. Therefore, the risk is high next to obstacles and lessens as the distance increases. Figure 7 visually represents the risk cost in a particular map example.



(**a**) (**b**)

Figure 7. Correspondence between a real map and its risk value map. The real map is displayed in (**a**). In (**b**) the risk is displayed using a gradient from white to black color (white represents the lowest risk and black represents the highest risk). The highest risk appears near the walls of the obstacles.

The risk function is described by the following equation:

$$risk(M, q, r) = 1 + \psi^2 O(M, q, r) \tag{3}$$

where M represents our labeled quadtree-based grid map, q represents the robot configuration, ψ represents the map resolution and $O(M, q, r)$ returns the amount of occupied cells around the given configuration q up to a distance r.

By optimizing the integral of the risk we achieve two goals simultaneously:

- Shorter paths are preferred.
- Paths that navigate far from the obstacles are preferred.

3.5. Trajectory Tracking (Act)

Once the path that allows the vehicle to reach the selected viewpoint has been computed, a line of sight (LOS) trajectory tracking controller [29] is used to follow it with minimum error. When the vehicle approaches the target viewpoint, the trajectory tracking controller is stopped and the vehicle is oriented according to the orientation of the viewpoint. Due to the thrusters configuration in the robot and the trajectory tracking controller used, lateral currents can affect the trajectory tracking performance. However, the control problem with water currents is out of the scope of this work. From our experimental experience, the selected approach can operate with lateral currents of up to 0.3 m/s, which is sufficient for the autonomous tasks shown in this work.

3.6. Summary of the Algorithm

Algorithm 1 summarizes the proposed robotic exploration approach. Lines 3 to 6 represent Sections 3.1 and 3.2. Lines 7 to 11 correspond to Section 3.3 and line 12 corresponds to Section 3.4. Finally, Section 3.5 is represented by line 13.

Algorithm 1: Exploration methodology

```
Input: Range measurements, robot position.
Output: Exploration trajectory, map.
begin
    while not shutdownRequested () do
        /* Sense                                                              */
        foreach measurement ∈ getNewMeasurements () do
            filtered_measurement = filterMeasurement (measurement)
            map.updateOccupancy (filtered_measurement)
        map.updateViewed (getRobotConfiguration ())

        /* Plan                                                               */
        range_candidates = map.getRangeCandidates ()
        camera_candidates = map.getCameraCandidates ()
        range_viewpoints = getRangeViewpoints (map, range_candidates)
        camera_viewpoints = getCameraViewpoints (map, camera_candidates)
        best_viewpoint = selectBestViewpoint (getRobotConfiguration (), range_viewpoints, camera_viewpoints)

        path = planPath (getRobotConfiguration (), best_viewpoint, map)

        /* Act                                                                */
        controller.sendPath(path)
        profiler.updateOrientation(best_viewpoint)

        /* Check if done                                                      */
        if map.mapped () or map.outsideLimits () or timeoutExpired () break
```

Figure 8 depicts the sequence of operations performed by the proposed exploration algorithm in a particular example.

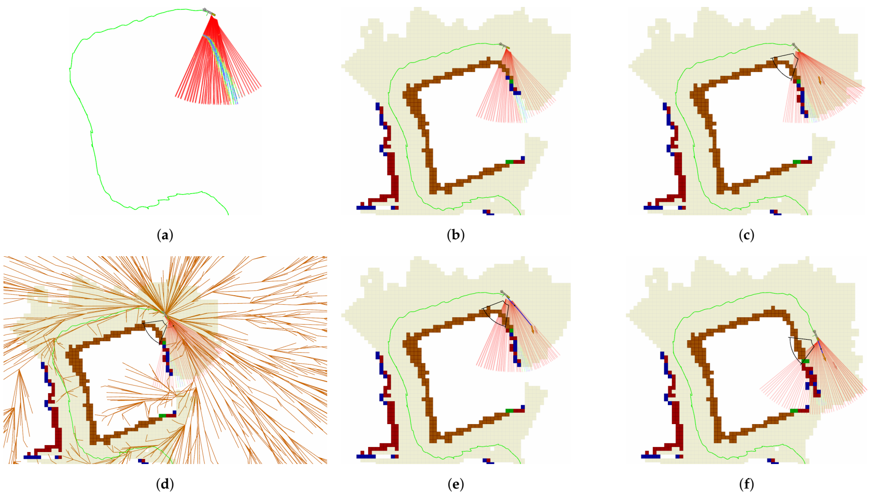


Figure 8. Sequence of operations performed by the proposed robotic exploration algorithm: (**a**) Initially the robot receives data from the sonar sensor. (**b**) The data is incorporated into the map. (**c**) The best view is selected. (**d**) A safe path is computed from the robot configuration to the selected viewpoint. (**e**) The path (blue line) is followed by the trajectory tracking controllers. (**f**) Finally, the robot reaches the viewpoint. By then, the map has changed and new viewpoints are generated to continue the exploration.

4. Experimental Platform

To validate the proposed robotic exploration algorithm we have used the Sparus II AUV (see Figure 9). This robot has two horizontal and one vertical thruster, allowing for partial hovering capabilities. The surge, heave and yaw degrees of freedom (DOFs) are actuated while the sway, roll and pitch DOFs are underactuated. It has a diameter of 0.23 m and it is 1.6 m long. It is rated for a maximum depth of 200 m. It has a 1.4 kWh battery which allows between 8 and 10 h of operation. Regarding the onboard computer, this particular robot has a dual core i7 CPU with 8 Gb of RAM. To estimate its position and orientation, the vehicle has a Doppler velocity log (DVL) sensor, an attitude and heading reference system (AHRS), a pressure sensor, and a global positioning system (GPS) sensor to receive fixes at surface. Further information regarding the vehicle can be found in Carreras et al. [30].

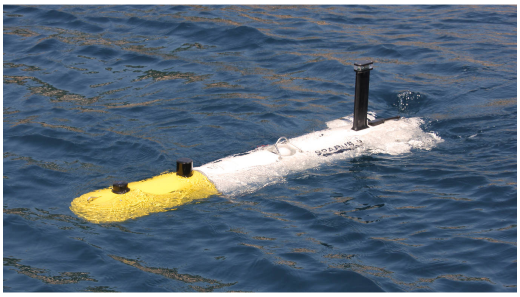


Figure 9. Sparus II AUV, a torpedo-shaped robot with partial hovering capabilities. It has been used to validate our robotic exploration algorithm.

The front part of the vehicle is the payload area, where the cameras and the scanning profiling sonar have been installed.

By means of a mechanically rotating beam, the sonar FOV spans 120 degrees. Although the robot is oriented according to the viewpoint, the FOV of the profiling sonar is also dynamically adjusted during the mission, so that it points towards the exploration target, while always covering the front of the vehicle. Figure 10 shows a representation of the FOV of all sensors.

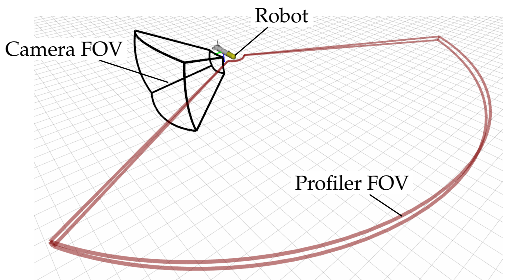


Figure 10. The camera FOV is represented by the black frame (the camera is oriented towards the right side of the vehicle), and the profiling sonar FOV is represented by the red frame (covering mainly the front part of the vehicle).

Throughout this work we have used GoPro Hero 4 Black cameras (GoPro, San Mateo, CA, USA) to acquire the images used for the reconstruction purposes (the optical reconstruction procedure, described in Hernandez et al. [31], is out of the scope of this work, but it is useful for us to demonstrate that the algorithm ensures full optical coverage according to the obtained map). A set of three cameras have been used, positioned at the front of the vehicle and oriented in the right, right-down and forward-right-down directions. Although the exploration algorithm planned the viewpoints for the right oriented camera, the other cameras maximized the optical coverage while maintaining the ability to perform feature matching between the obtained images. No artificial light has been used for the experiments presented in this work, but it could be used during low visibility operations.

The proposed algorithm has been implemented using the C++ programming language, and it has been connected to the rest of the robot's software architecture using the robot operating system (ROS) [32]. Figure 11 shows the interconnections between the different parts of the proposed exploration method.

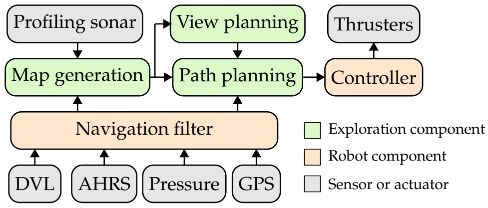


Figure 11. The modular design of our proposal eases integration with typical robotic software architectures. The green blocks are the components developed in our proposal. They interact with the profiling sonar sensor, the vehicle controller and the navigation block. The navigation block is in charge of the localization of the vehicle through dead reckoning, using a Doppler velocity log (DVL) sensor, an attitude and heading reference system (AHRS), a pressure sensor and a global positioning system (GPS) sensor.

5. Experimental Outcomes

The proposed robotic exploration algorithm has been validated in three different scenarios. The first scenario corresponds to a series of breakwater concrete blocks, which provide a challenging testing environment because of its narrow passages. The second scenario is an isolated rock next to the coast cliffs. This natural environment has been used to test the algorithm so that it can explore targets with complex geometry. Finally the algorithm has also been tested at 28 m depth by exploring an underwater seamount. In this section the obtained exploration trajectories and their corresponding 3D optical reconstructions are presented and discussed.

5.1. Breakwater Blocks

The first scenario is a series of breakwater concrete blocks located outside the harbor of St. Feliu de Guíxols, Girona. The size of each block is approximately 12×12 m. It is a man-made scenario presenting a simple geometry. However, due to its narrow passages, it is a challenging scenario for underwater exploration. Figure 12 shows an aerial view of this site and Figure 13 shows the Sparus II AUV during an autonomous mission in the breakwater blocks.

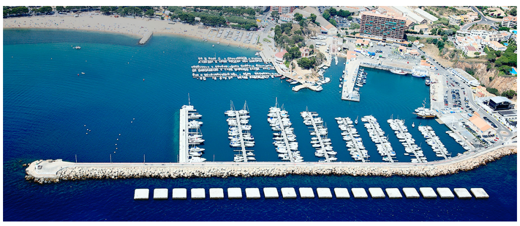


Figure 12. Aerial view of the harbor of St. Feliu de Guíxols. The breakwater blocks can be seen at the bottom part of the image.

Figure 13. Sparus II AUV performing an autonomous mission in the blocks environment.

The robot performed the mission at a depth of 1.75 m, allowing for the use of a surface buoy with a Wi-Fi connection, which was used for visualization and safety purposes. The exploration trajectory was about 100 m long and the maximum surge speed was 0.3 m/s. Figure 14 shows the robot trajectory during an autonomous exploration of the breakwater blocks.

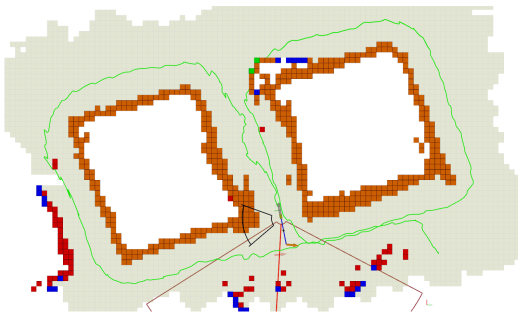


Figure 14. Real inspection of two breakwater concrete blocks. Each block spans an area of approximately 12 $\times$ 12 m. The robot trajectory began in front of the block that appears on the right side of the image.

As it can be seen, the robot's estimated position drifted. The shape of the blocks is distorted and some of the walls appear twice in the map. However, correcting the localization drift is out of the scope of this work. At the same time, localization drift can be assumed to accumulate over time, so is usually low in areas that have been recently explored, and high in areas that have been previously explored and are revisited after some time. Since the vehicle normally operates near areas that have been recently explored, some navigation drift can be tolerated without negatively affecting the performance of the algorithm. Finally, Figure 15 shows the optical reconstruction obtained in the Breakwater blocks scenario.

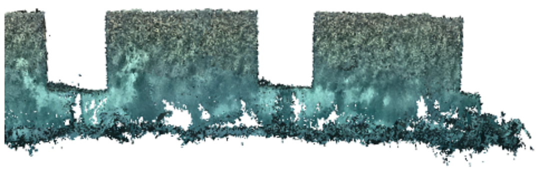


Figure 15. Reconstruction of the breakwater blocks using optical data.

This scenario has been extensively used to test our previous versions of the the presented approach. In Vidal et al. [8] the robot was able to autonomously explore 8 consecutive blocks.

This demonstrated that our method is suitable for man-made structured environments. However, the approach used in [8] had safety issues which caused the robot to navigate too close to the concrete blocks in some circumstances. In this work, only safe viewpoints are used for exploration, leading to safer exploration trajectories.

5.2. Punta del Molar

The second scenario corresponds to an isolated rock located next to the coast cliffs of St. Feliu de Guíxols, Girona. Figure 16 shows a satellite view of this site. The rock is about 60 m with a variable and irregular width.

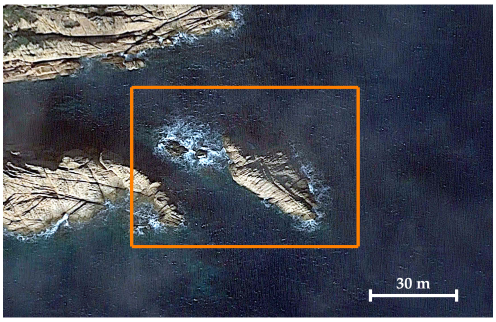


Figure 16. Satellite view of Punta del Molar, *Google Earth, 2017*. The coast cliffs can be seen at the top and left sides of the image.

Figure 17 shows the robot trajectory during the exploration of Punta del Molar. This mission was performed at a depth of 2.5 m, also allowing for a safety Wi-Fi buoy. The full exploration took 17 min and the traveled distance was around 170 m.

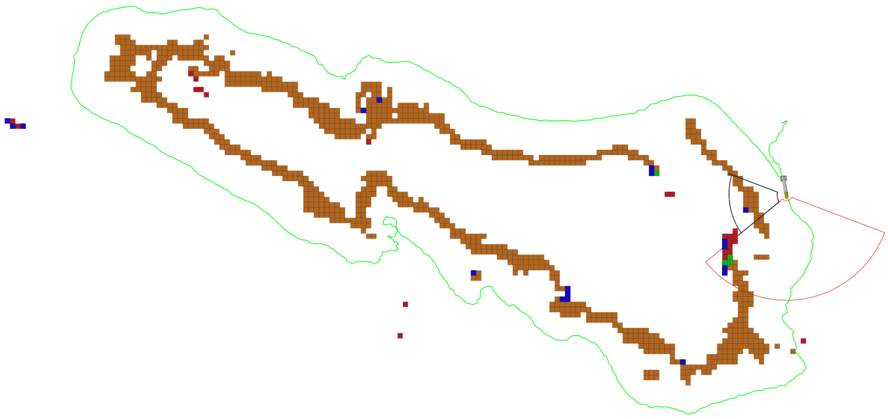


Figure 17. Real experiment showing the inspection of a natural rock surrounded by water near the coast cliffs. The rock is approximately 60 m long (please, see Figure16). The inspection trajectory ended near the initial point, following the rock clockwise. This is the result of having the cameras mounted pointing towards the right hand side of the robot. In this figure, empty space cells are not represented.

For this scenario a 3D reconstruction has also been performed. It is shown in Figure 18. In this case, due to accumulated drift and poor visibility, the optical reconstruction pipeline was not able to close the loop and provide a complete 3D model.

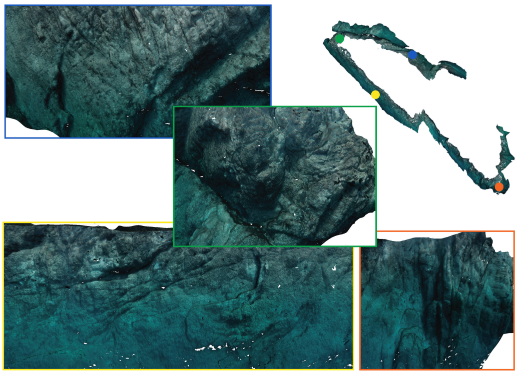


Figure 18. Optical reconstruction of the Punta del molar environment.

The experiments in this scenario show that the algorithm is suitable for natural unstructured environments.

5.3. Amarrador Seamount

The Amarrador seamount is a 12 m high underwater seamount, rising from 40 m depth. Its base spans an area of 15 × 30 m. This natural environment has been used to demonstrate that the algorithm is able to explore targets with complex geometry. Furthermore, it is located in an area with strong currents of up to 0.5 m/s, which makes operations more difficult.

In order to autonomously find the Amarrador seamount (only an approximate GPS position was available) and trigger the exploration algorithm, the AUV performed the following sequence of actions:

1. The robot navigates to the diving location, which is located at a distance from the target.
2. The robot dives to the desired exploration depth.
3. The robot performs a spiral maneuver around the expected underwater boulder location to localize the structure.
4. When the sonar detects the structure, the proposed robotic exploration algorithm is triggered.
5. The exploration finishes once the map is complete or when a timeout has expired.

This sequence of actions is tailored for this specific scenario and it is not part of the presented algorithm. The procedure was first tested in simulation. Figure 19 shows a picture of the robot exploring the seamount in simulation.

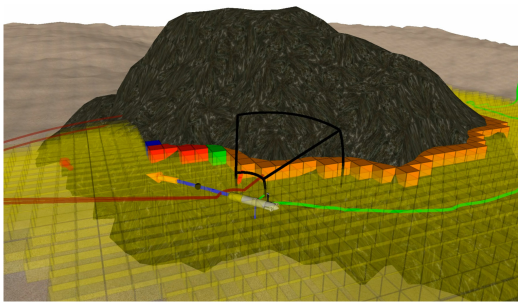


Figure 19. Simulated exploration of the Amarrador seamount.

Then, the approach was tested in real sea experiments. Several autonomous missions were successfully performed using Sparus II AUV. Figure 20 shows different successful exploration missions, and Figure 21 shows the evolution of one of the missions to help understanding the sequence of maneuvers that are performed.

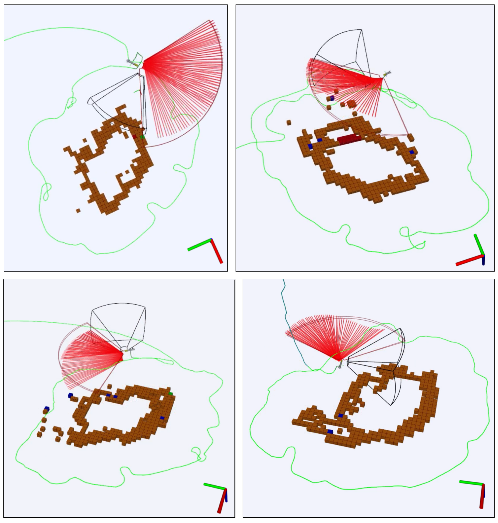
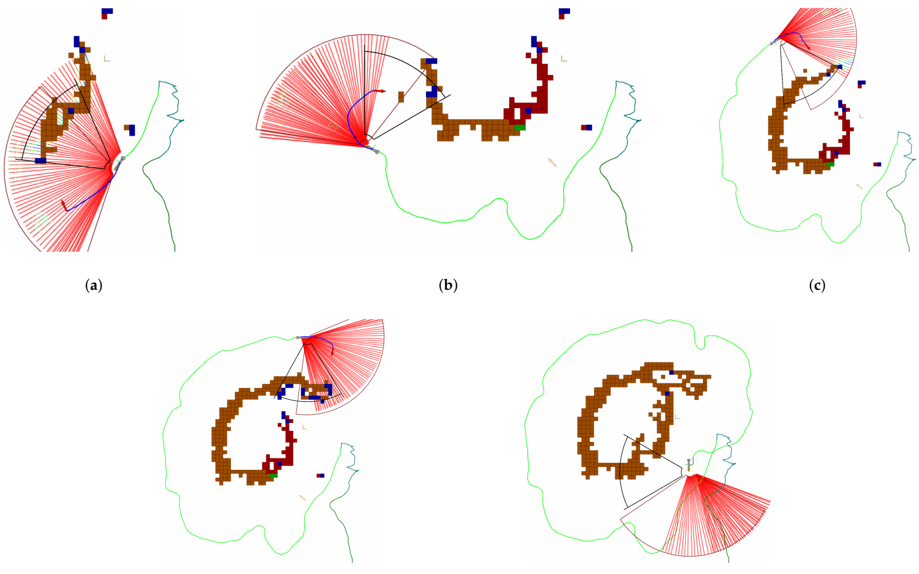


Figure 20. Experimental results in the Amarrador seamount. The four images depict the trajectory of four different successful missions conducted with Sparus II AUV. The robot autonomously explored the underwater seamount in 2D, circumnavigating the rock while keeping the distance suitable for data acquisition. The orientation of each image has been adapted to better visualize the map. Red axis is north, green axis is east, and blue axis is down.



(**a**) (**b**) (**c**)

(**d**) (**e**)

Figure 21. Different captures during a real exploration of the Amarrador seamount. In (**a**) the robot finds the seamount and starts mapping it. Then, in (**b**–**d**) the robot keeps going to the next best view to keep the exploration going. Finally, in (**e**) the robot has a complete map, so no more viewpoints can be generated. The mission is finished.

Finally, Figure 22 shows different images obtained from the cameras during the autonomous exploration mission, and Figure 23 shows the reconstruction of the Amarrador seamount. The images show the obtained textured 3D model from different angles.

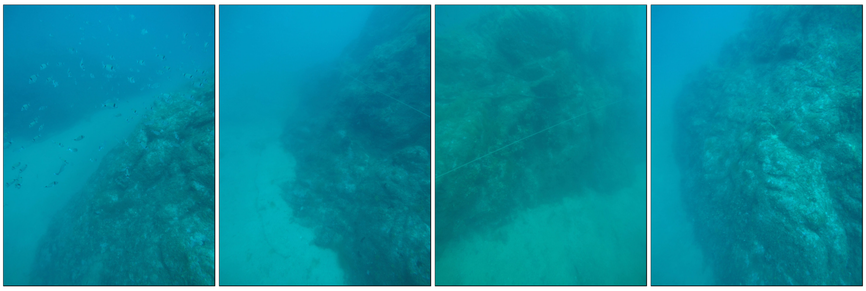


Figure 22. Different images obtained during autonomous exploration missions of the Amarrador underwater boulder. The robot performed the exploration at a depth of 28 m, and the distance between the robot and the rock was 5 m.

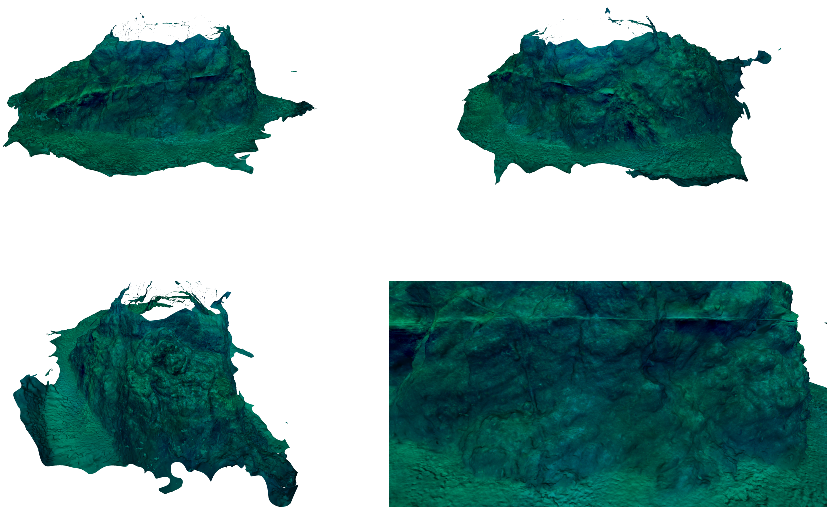
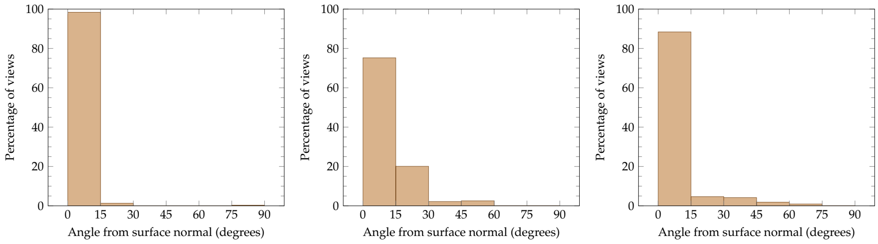


Figure 23. Using the images acquired during a 2D autonomous exploration of the Amarrador seamount, a 3D reconstruction has been obtained. The geometry is presented with the texture extracted from the same images.

These experiments are also a proof of reliability. Since the missions were performed at depth of 28 m, it was not possible to use a buoy with a high bandwidth Wi-Fi connection. Only acoustic communication was available during the experiments.

5.4. Quantitative Evaluation

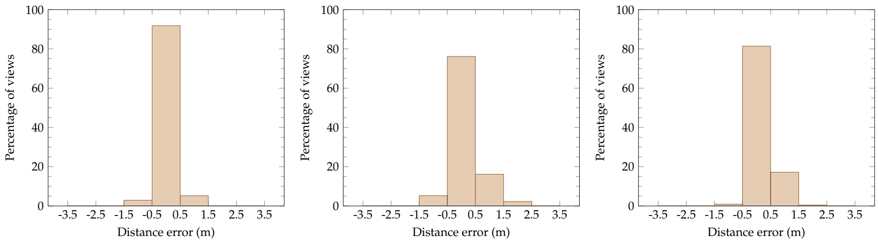
As stated in Section 3, the viewpoints are placed so that images are obtained along the direction of the surface normal (small incidence angle). After all datasets have been acquired, the incidence angle has been evaluated in an offline procedure. Figure 24 represents the distribution of the best incidence angle for each viewed cell in the final map. In the breakwater blocks scenario, 98% of the viewed cells had been imaged with an incidence angle between 0 and 15 degrees. This measure decreases for environments with higher geometrical complexity. In the Punta del Molar, 75% of the viewed cells were imaged with an incidence angle between 0 and 15 degrees, and for the Amarrador seamount this measure increases to 88%. It is also important to remark that in all scenarios, more than 95% of the viewed cells have been observed within ±5% degrees from the central part of the camera's FOV.



(**a**) Breakwater blocks (**b**) Punta del Molar (**c**) Amarrador seamount

Figure 24. Histograms of the angles between the surface normal and the observation angle for all scenarios (**a**–**c**). Most viewed cells have been observed from a direction close to the surface normal.

The distance from which each viewed cell has been observed has also been analyzed. Figure 25 shows histograms of the distance error for each scenario. In the breakwater blocks, 92% of the viewed cells were imaged from a distance within 0.5 m from the target distance. For the Punta del Molar and Amarrador scenarios, this value is 76% and 81%, respectively.



(**a**) Breakwater blocks (**b**) Punta del Molar (**c**) Amarrador seamount

Figure 25. Histograms of the distance errors (distance between the target distance δ and the best observation distance) for all scenarios (**a**–**c**). Most viewed cells have been observed from a distance close to the desired distance.

6. Conclusions and Further Work

In this work we have presented a 2D frontier-based viewpoint generation algorithm for exploration using AUVs. While most of the existing underwater literature is focused on CPP algorithms, where previous information such as a rough map is used to plan coverage trajectories, our proposal does not require prior information and it is able to explore unknown 2D environments with elements of high relief.

The main contributions of this work are: (1) A novel 2D exploration algorithm which accounts for occupancy and optical data coverage simultaneously. (2) The combination of FB and view planning ideas in a single algorithm while keeping the computational requirements low. (3) Experimental evaluation through different sea trials, including a the breakwater concrete blocks, the Punta del Molar and the Amarrador scenarios, also showing a possible application such as 3D seabed reconstruction.

Further work will focus on finding an exploration strategy for the case where no initial viewpoints can be generated. We also plan to extend the algorithm to 3D environments, where we will use a multibeam sensor mounted in a tilting device on the Girona 500 AUV (see Ribas et al. [33]). Additionally, we would also like to expand the algorithm to be able to take into account viewpoints for multiple cameras.

Our robotic exploration system would also benefit from a SLAM back-end to correct the drift present in the dead reckoning navigation of our vehicle. In this regard, Guillem et al. [34] has already used datasets, obtained with the previous version of the presented approach, to test a SLAM back-end. Having live feedback from the cameras would also open new possibilities for active localization/navigation and SLAM. Finally, modeling the uncertainty in the environment with probabilistic methods could be useful to improve the consistency of the map and the generation of next best viewpoints.

Author Contributions: The work presented in this paper was carried out in collaboration with all authors. E.V., with the collaboration of M.C. and N.P., designed and implemented the frontier-based viewpoint generation algorithm for robotic exploration, and tested it in different scenarios. E.V., with the collaboration of J.D.H., developed the motion planning part of the presented algorithm. K.I. processed the images acquired during the exploration missions to obtain the presented 3D reconstructions. All authors have helped in the writing/review and editing of this document.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

2D	2-dimensional
2.5D	2.5-dimensional
3D	3-dimensional
AGP	art gallery problem
AHRS	attitude and heading reference system
AUV	autonomous underwater vehicle
AUVs	autonomous underwater vehicles
CIRS	underwater robotics research center
CPP	coverage path planning
DOF	degree of freedom
DOFs	degrees of freedom
DVL	Doppler velocity log
FB	frontier-based
FOV	field of view
FOVs	fields of view
GPS	global positioning system
ICS	inevitable collision state
ICSs	inevitable collision states
LOS	line of sight
MAV	micro aerial vehicle
MAVs	micro aerial vehicles
NBV	next-best-view
OMPL	open motion planning library
PDN	perception-driven navigation
PID	proportional-integral-derivative
RA	reactive algorithm
RAs	reactive algorithms
ROS	robot operating system
ROV	remotely operated vehicle
ROVs	remotely operated vehicles

RIG	rapidly-exploring information gathering
RRT	rapidly-exploring random tree
RRT*	asymptotic optimal rapidly-exploring random tree
SAS	synthetic aperture sonar
SLAM	simultaneous localization and mapping
TSP	traveling salesman problem
UAV	unmanned aerial vehicle
UAVs	unmanned aerial vehicles
UdG	university of Girona
UGV	unmanned ground vehicle
UGVs	unmanned ground vehicles
USBL	ultra-short baseline
VICOROB	computer vision and robotics group
VP	view planning

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5

Online Multilayered Motion Planning with Dynamic Constraints for Autonomous Underwater Vehicles

In this chapter, we propose a start to goal motion planner for autonomous underwater vehicles to enhance the planning capabilities within the exploration algorithm. The planner is able to compute a trajectory from the start configuration to the goal configuration that accounts for the vehicle dynamics and water currents, while reducing the planning time to enable its use for online planning. The publication in this chapter was developed in collaboration with the Kavraki Lab, Houston, USA.

Title: Online Multilayered Motion Planning with Dynamic Constraints for Autonomous Underwater Vehicles
Authors: **Eduard Vidal**, Mark Moll, Narcís Palomeras, Juan David Hernández, Marc Carreras, and Lydia E. Kavraki
Proceedings: IEEE International Conference on Robotics and Automation (ICRA)
Volume: –, Number: –, Pages: –, Published: 2019
Quality index: Not a journal

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Abstract

Underwater robots are subject to complex hydro-dynamic forces. These forces define how the vehicle moves, so it is important to consider them when planning trajectories. However, performing motion planning considering the dynamics on the robot's onboard computer is challenging due to the limited computational resources available. In this paper an efficient motion planning framework for autonomous underwater vehicles (AUVs) is presented. By introducing a loosely coupled multilayered planning design, our framework is able to generate dynamically feasible trajectories while keeping the planning time low enough for online planning. First, a fast path planner operating in a lower-dimensional projected space computes a lead path from the start to the goal configuration. Then, the lead path is used to bias the sampling of a second motion planner, which takes into account all the dynamic constraints. Furthermore, we propose a strategy for online planning that saves computational resources by generating the final trajectory only up to a finite horizon. By using the finite horizon strategy together with the multilayered approach, the sampling of the second planner focuses on regions where good quality solutions are more likely to be found, significantly reducing the planning time. To provide strong safety guarantees our framework also incorporates the conservative approximations of inevitable collision states (icss). finally, we present simulations and experiments using a real underwater robot to demonstrate the capabilities of our framework.

6

Multisensor Online 3D View Planning for Autonomous Underwater Exploration

In this chapter, we present the final version of our 3D VP algorithm for autonomous underwater exploration. In this publication, we present the details of the 3D exploration alorithm, and we also report extensive experimental evaluation using the Girona 500 AUV in different scenarios. This work has been submited to the Journal of Field Robotics.

Title: Multisensor Online 3D View Planning for Autonomous Underwater Exploration
Authors: **Eduard Vidal**, Narcís Palomeras, and Marc Carreras
Submitted to: Journal of Field Robotics
Quality index: Submitted to JCR2017 Robotics, Impact Factor: 3.46, Q1

Multisensor Online 3D View Planning for Autonomous Underwater Exploration

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Abstract

This work presents a novel octree-based 3-dimensional (3D) exploration and coverage method for autonomous underwater vehicles (AUVs). Robotic exploration can be defined as the task of obtaining a full map of an unknown environment with a robotic system, achieving full coverage of the area of interest with data from a particular sensor or set of sensors. While most robotic exploration algorithms consider only occupancy data, typically acquired by a range sensor, our approach also takes into account optical coverage, so the environment is discovered with occupancy and optical data of all discovered surfaces in a single exploration mission. In the context of underwater robotics, this capability is of particular interest, since it allows to obtain better data while reducing operational costs and time. This works expands our previous work in 3D underwater exploration, which was demonstrated through simulation, presenting improvements in the view planning (VP) algorithm and field validation. Our proposal combines VP with frontier-based (FB) methods, and remains light on computations even for 3D environments thanks to the use of the octree data structure. Finally, this work also presents extensive field evaluation and validation using the Girona 500 AUV. In this regard, the algorithm has been tested in different scenarios, such as a harbor structure, a breakwater structure and an underwater seamount.

SUBMITTED PAPER. EMBARGO UNTIL PUBLICATION DATE

7

Results and Discussion

In this chapter the main results of the thesis are discussed. Section 7.1 provides a summary of the completed work. Next sections discuss the results obtained along the roadmap of the thesis: Section 7.2 discusses the results regarding the 2D version of the algorithm, Section 7.3 discusses the results of the multilayered motion planning work and Section 7.4 comments the results regarding 3D exploration. In order to avoid excessive repetition with the result sections of the publications of this compendium, the reader is referred to the corresponding chapter where the detailed results can be found for each section, and we focus in providing additional insights on the decisions taken and reasoning behind the tests that have been performed.

7.1 Summary of completed work

In this thesis we have developed a robotic exploration algorithm for underwater vehicles. The main goal has been to develop an algorithm which provides these vehicles with the required autonomy to fully map a completely unknown environment with range data and optical data in a single mission. To do so, we have combined VP with FB techniques to come up with a novel algorithm suitable for the underwater domain. Furthermore, all the publications in this compendium include real experiments performed either with the Sparus II AUV or with the Girona 500 AUV, to demonstrate and validate our proposals.

In Chapter 2, we presented the initial work developed in this thesis as a key element to provide autonomy to the Sparus II AUV, in the context of the motion planning work developed in the CIRS lab. The VP work is presented as an evolution of the start to goal motion planning line, previously developed in the lab.

In Chapter 3, we proposed a 2D VP algorithm for underwater exploration. It explains in detail the basic concepts behind the algorithm, from the map generation and the different labels in the map, to the VP and motion planning aspects. In this publication, experimental results using Sparus II AUV are reported, showing 2D autonomous explorations of a harbor area and a breakwater structure.

In Chapter 4, we presented the improved version of the 2D algorithm. In this publication, we redesigned the different cell labels, we proposed the use of the quadtree data structure to store the map, and we proposed a method to minimize the effects of the sonar false negative measurements. This publication also reported experimental results in the Amarrador underwater boulder.

In Chapter 5, we developed a start to goal motion planner for autonomous underwater vehicles, which accounts for the vehicle dynamics and water currents while keeping the planning time low enough for online planning applications. The motion planner is based on a multilayered scheme where an RRT* planner computes a lead path that is then used to bias the sampling of a SST motion planner, which generates the dynamically feasible trajectory. This work was developed during a research stay carried out in the Kavraki Lab, Houston, USA, under the supervision of Lydia Kavraki.

Finally, in Chapter 6, we presented the last version of the algorithm, which is able to guide the Girona 500 AUV so that it explores a 3D environment. This publication presented in detail the 3D algorithm and all its improvements, and added extensive experimental evaluation. Results were reported in three different scenarios: a harbor area, a breakwater structure, and an underwater boulder. This publication also contains an updated review of the state of the art in underwater robot exploration.

The general approach behind this thesis' proposal has been determined by many factors: the previous experience in motion planning gathered by the CIRS lab, the general knowledge regarding autonomous underwater robots, the goal of having an online system that provides autonomy to the vehicle, the understanding of data structures and their effect to the performance of algorithms, and the study of the state of the art in the field of robotic exploration.

7.2 2D underwater exploration using Sparus II AUV

The motivation behind the development of this thesis was to provide the AUVs with the capability to autonomously explore an unknown region of the environment, obtaining an occupancy map and images in a single exploration mission. One of the first steps was to choose a platform and a payload. Between the two available robots in the CIRS lab, the Sparus II AUV was chosen because of its reduced weight and size, and its generic torpedo shape. In order to sense the environment, a scanning profiling sonar was selected, as it was suitable for the available payload capacity in the Sparus robot. This setup allowed the development of a 2D exploration algorithm, but was not enough for 3D exploration. To gather images from the environment, a set of isolated cameras was the most flexible and effective solution. However, that meant that the exploration algorithm could not rely on having a live stream of images. The publication of Chapter 2 provides many details regarding the use of the Sparus II AUV as a platform for underwater exploration.

To represent the environment several options were available. The grid map approach was chosen because it is a common map representation, widely used in the robotics community, and also because it was easy to extend to 3D environments. Other vectorial representations, such as polygon-based maps, were discarded.

During the development of the 2D exploration algorithm, a set of cell labels had to be chosen. Our initial selection of cell labels is described in the publication of Chapter 3, in Section III.A. After gathering valuable information in the second publication of this compendium, we decided to eliminate the *Occplane* cell label, as it was not useful from the perspective of the VP algorithm. Instead, we decided to add candidate cells for each sensor type, a novel idea that allowed us to plan for different types of sensor. The updated selection of cell labels is detailed in the publication of Chapter 4, in Section 3.1. It is possible to further extend this approach to incorporate extra sensors. In that scenario, new cell labels would be required, and the algorithm would track the coverage of the environment with the new sensor, generating new frontiers and new viewpoints, which will be also candidates for exploration.

In this part, we also had to develop a strategy to actively reorient the scanning profiling sonar beam so that its FOV always covered the front part of the vehicle and also the candidate cell. This behavior was introduced after real experimentation, where we detected that the robot had difficulties when mapping the corners of the breakwater blocks structure. This strategy is described in the publication of Chapter 3, in Section III.G.

To improve the path planning capabilities of the system, a 2D motion planner based on the asymptotic optimal rapidly-exploring random tree (RRT*) was developed. RRT* was chosen over other planners such as A* because of its speed, adaptability, and because several examples showed that it was going to perform well in 3D. We decided to use the open motion planning library (OMPL). The integration of the OMPL RRT* with the exploration algorithm is detailed in the Section III.E of the publication of Chapter 3.

Even in 2D, we soon realized that storing the map as a fixed size array of cells was not a good solution. The memory requirements were relatively low in the 2D case, but they would have been unmanageable in the 3D case. Furthermore, it was difficult to access the cells of each label in isolation, and nearest neighbor searches were really slow. To solve all those issues, we decided to use the quadtree data structure to store our 2D map. We decided to use several quadtrees to store the data of the different labels in the map, allowing the access of the cells of each label individually, and also enabling the possibility to perform isolated nearest neighbor queries. Standard tree based mapping tools did not provide nearest neighbor capabilities, so at this early stage of the thesis, we decided that it was worth to develop our own implementation of the quadtree data structure, specifically tailored to our needs. The use of the quadtree data structure in the exploration algorithm is explained in Section 3.1 of the publication of Chapter 4.

After experimentation with the robot and profiling sensor, we realized that false negative sonar measurements led to false empty space behind the obstacles in the map, which was causing viewpoints to be generated in inaccessible locations. The generation of viewpoints in inaccessible locations initially led to erratic behavior, and some missions had to be aborted because of the generation of an invalid or too dangerous viewpoint. At first, we solved the problem by periodically checking for continuity of empty space using a region growing algorithm. However, this was computationally very expensive, as it was an inefficient way to solve the fully dynamic connectivity problem, which led to the development and publication of the noise filtering strategy. The proposed noise filtering strategy allowed to discard invalid and dangerous viewpoints at a very early stage, and resulted in a significant improvement in the viewpoint generation process and the robustness of the overall algorithm. In this compendium, the most detailed explanation of the noise filtering strategy can be found in Section 3.2 of the publication in Chapter 4.

The noise filtering approach counts the amount of empty and occupied detections and discards the empty detections that do not agree with the rest of neighboring cells. Then, the hit and miss approach is used to obtain the final occupancy state of a cell. Equation 7.1 shows how the hit and miss ratio is computed.

$$r = \frac{occupieds}{empties + occupieds} \tag{7.1}$$

where r is the ratio between occupied detections and total detections.

Then, a cell is occupied if $r \geq th$ and empty if $r < th$, where th is a user defined threshold.

Alternatively, other common Bayesian approaches such as the Octomap library [31] apply the log-odds formulation of Equations 7.2 and 7.3.

$$L_0 = L_{init} \tag{7.2}$$

$$L_n = \max(\min(L_{n-1} + L_{measurement}, L_{max}), L_{min}) \tag{7.3}$$

where L_{init} corresponds to the log-odds of the prior occupancy probability, L_{max} and L_{min} are the clamping parameters, and $L_{measurement}$ corresponds to the log-odds of the measurement probability (either L_{empty} or $L_{occupied}$).

Then, a cell is occupied if $L_n > th_1$ and empty if $L_n < th_0$, where th_1 and th_0 are user defined thresholds.

If there is no clamping ($L_{max} = +\infty$ and $L_{min} = -\infty$), the thresholds are set as $th_0 = th_1 = 0$, and the prior is set at 0.5 ($L_{init} = 0$), Equations 7.2 and 7.3 become Equation 7.4.

$$L_n = L_{empty}\, empties + L_{occupied}\, occupieds \tag{7.4}$$

As shown by Equation 7.5, it is possible to obtain a threshold for the hit and miss approach that achieves the same behavior as the Bayesian approach under the aforementioned parameters and conditions. Because of that, although not formulated through Bayesian probabilities, the approach described in this thesis is comparable in its behavior to some of the widely used Bayesian mapping strategies.

$$th = \frac{1}{1 - \frac{L_{occupied}}{L_{empty}}} \tag{7.5}$$

To convert from log-odds formulation to a probability p from 0 to 1, with 0 being empty and 1 being occupied, the Equation 7.6 can be used.

$$p = \frac{\exp_2(L)}{1 + \exp_2(L)} \tag{7.6}$$

Furthermore, since the amount of empty and occupied detections is available to compute the probability of occupancy at any time, it is possible to also obtain the entropy and apply information-theoretic techniques, for instance, to the viewpoint selection process. The entropy H can be obtained using Equation 7.7.

$$H = -p \log_2(p) - (1 - p) \log_2(1 - p) \tag{7.7}$$

To select the next best viewpoint, a common strategy is to compute the expected entropy reduction caused by the exploration of each candidate viewpoint, choosing then the viewpoint that has the maximum entropy reduction. Preliminary results in this direction can be found in Appendix A, where this information-theoretic approach has been compared with the method proposed along this thesis.

Map inconsistencies are a consequence not only of sonar measurement noise, which is filtered through the proposed noise filtering strategy, but also of the localization drift. When the vehicle's localization drifts, the generated map becomes inconsistent and artifacts appear, which may cause the robot to take inefficient exploration decisions. Because the focus of this thesis was not the vehicle's localization, to avoid the aforementioned problem, several actions have been conducted:

- The vehicle's localization has been computed using an extended Kalman filter (EKF), an efficient and robust method to combine the measurements of the different localization sensors.

- The maximum duration of the missions has never exceeded 90 minutes. By having a limited duration of the missions, the maximum localization drift is also limited.

- The safety behaviors of the vehicle have been given absolute priority to avoid colliding with the environment.

In the narrow corridors between the breakwater blocks, and in some parts of the Amarrador underwater boulder, we have detected sonar multi-path. However, the artifacts produced by multi-path have not had a negative effect on the algorithm's ability to explore the environment.

Finally, the 2D algorithm has been tested in different scenarios, all of them with elements of high relief so that a slice can be chosen to perform a 2D exploration. Results in a harbor environment and in the breakwater structure are reported in Section IV of the publication of Chapter 3. Those results demonstrated the validity of the proposed approach in structured environments. Then, in Chapter 4, Section 5 of the publication presents results in the Punta del Molar rock and the Amarrador underwater boulder. Those experiments demonstrated the performance of the algorithm in unstructured environments. Furthermore, only acoustic communication was available for the Amarrador experiments, which demonstrated the reliability of the algorithm. The robot obtained images of the underwater boulder from a very close distance, and the publication also shows a 3D reconstruction of the site.

7.3 Motion planning with nonlinear dynamics and water currents

Underwater robots have nonlinear dynamics, and often suffer from motion constraints imposed by their design and thruster configuration. Water currents also affect the controller's tracking performance, which can corrupt the data obtained from the environment or even put the robot in a dangerous situation.

During the research stay in the Kavraki Lab, we developed a start to goal motion planner for systems with nonlinear dynamics, which also accounts for water currents. Start to goal planning is a core element in the exploration algorithm, as it allows the robot to compute a safe trajectory from its current configuration to the target viewpoint, avoiding collisions with the obstacles in the map. To avoid collisions, the planner uses a risk function that is updated after each sensor measurement, which happen several times every second.

While other planning methods were either too slow or too simple to account for the dynamics and water currents, the proposed method achieved the desired performance for our specific underwater planning problem.

To achieve the desired performance we proposed a multilayered solution. The main idea behind the proposed planning solution is to have two motion planners. One of them computes an approximate geometric lead path in a lower-dimensional space. Then, this lead path is used to bias the sampling of a second motion planner, which accounts for the full problem including the dynamics of the vehicle. The lead path helps focusing the search of the computationally expensive planner on regions that are more likely to contain good quality solutions. The details of the multilayered algorithm are given in Section III of the publication of Chapter 5 in this compendium.

There is a possibility that the lead path is generated where no dynamically feasible paths are possible. Because of that, it is important to always keep a percentage of uniform sampling, mixed with sampling near the lead path, so that probability completeness is maintained and the solution can always be found. If uniform sampling is also used, the space of solutions is not restricted.

The RRT* algorithm was selected as the planner used in the first layer because of our previous experience with it and its adaptability to different problems. We also considered it was a good candidate for 3D environments, where other graph-based algorithms such as A* could be too slow according to our tests. The stable sparse-RRT (SST) algorithm was selected as the planner used in the second layer because of its asymptotic near optimality, even in systems with nonlinear dynamics. Both planners are loosely integrated through the sharing of the lead path.

Although the framework is able to account for water currents, it is difficult to measure them and use them in reality. To do so, water current estimation techniques have to be used, which are out of the scope of this thesis. Because of that, this feature of the motion planner has been demonstrated only in simulation, where there is precise knowledge of the water currents introduced in the system.

We tested the proposed planning solution using the Sparus II AUV because it is more restricted in its movements than the Girona 500 AUV. The testing scenario was the breakwater structure composed of concrete blocks, located in St. Feliu de Guíxols. Results demonstrated that it is possible to achieve great convergence towards the optimal solution of the problem in less than 5 seconds. With this approach, the robot was able to navigate in close proximity to the blocks, reliably crossing from one side to the other, navigating in the narrow passages between the blocks. Results are reported in Section IV of the same publication in Chapter 5.

7.4 3D underwater exploration using Girona 500 AUV

For 3D underwater exploration, we decided to use the Girona 500 AUV because of its larger payload area and because of its high maneuverability. Instead of using a profiling sonar with only one mechanically scanning beam, a 3D payload was designed, incorporating a multibeam sonar mounted in a tilting device. Regarding the cameras, a set of cameras were mounted in the housing of an omni-directional camera developed at CIRS. The cameras were not connected to the computer, so live streaming of images was not available. In this compendium of publications, all details regarding the 3D exploration algorithm are given in Chapter 6. A description and images of the 3D payload are given at the beginning of Section 3 and in Section 4.

For the 3D explorations, the quadtree data structure was transformed into an octree data structure. A similar conversion happened for many 2D components in the view planner, such as the surface normal computation or the evaluation of the cells inside the FOV of the cameras, which were transformed to 3D. Similarly, the noise filtering strategy was extended to 3D. This meant that every cell in the map had 6 empty detection counters instead of 4, corresponding to all possible directions. All those components were adapted to the 3D map. This work is partially reported in Section 3.1.

The positioning of the viewpoints was improved, as sometimes they were generated near an obstacle. In the 2D algorithm, those viewpoints were discarded during the motion planning stage, which was a very slow approach. Because of that, we proposed the introduction of the safe and unsafe empty cells. With the introduction of safe empty cells, viewpoint repositioning was possible by projecting each viewpoint position to the nearest empty safe cell. However, not all reprojected viewpoints are valid, as some might have lost the ability to inspect their candidate cell. The 3D viewpoint generation process is detailed in Section 3.2.

The geometric motion planner based on the RRT* was also extended to 3D. The trajectory tracking controller based on the line of sight (LOS) strategy also had to be updated to track 3D paths, taking advantage of the available sway degree of freedom (DOF). This work corresponds to Sections 3.3 and 3.4.

After experimenting with different 3D environments, we realized that narrow passages caused viewpoints to be generated in inaccessible parts. Those parts are difficult to identify unless the motion planner is used. For that reason, we introduced the concept of blacklisted cells. If, after trying to reach a viewpoint for a sufficient amount of time the viewpoint has not been achieved, the candidate cell is blacklisted. Blacklisted cells recover their original state once all the other cells have been explored. Section 3.1 gives a detailed explanation of the introduction of the blacklisted cell label.

A very important aspect of the 3D exploration algorithm is the viewpoint cost function, which determines the best viewpoint to visit next. For the 3D case, a lot of experimentation was put to obtain a cost function that led to good results across all testing scenarios, while being simple to implement and to understand. As explained in the last publication of this compendium, we proposed to penalize deeper viewpoints, so that the robot explores the environment approximately following a top to bottom approach. The cost function that selects the best viewpoint is discussed in Section 3.2.

Finally, in the 3D algorithm we tackled a problem that we left unsolved in the 2D algorithm, which is the exploration strategy for cases where the currently explored area is empty. We solved the problem considering also as range candidates the cells in the frontier between unknown and empty cells. By doing so, viewpoints are generated so that the robot explores the boundary between empty space and unknown space, even if it is not next to an obstacle. However, as soon as an obstacle appears in the map, the frontier cells near the obstacle are automatically preferred, so that the object is mapped prior to the empty space. This aspect of the algorithm is introduced in Section 3.2.

The 3D algorithm has been tested in different scenarios, with different geometries. Section 5 in the paper shows the experimental outcomes. Section 5.1 shows the results in the harbor area, Section 5.2 shows the results in the breakwater structure, and Section 5.3 reports the results in the Amarrador underwater boulder. Those results are, as far as the authors are concerned, the first experiments showing a completely autonomous underwater exploration with sonar and cameras, where an AUV inspects an underwater structure from close proximity without human supervision. Many details are given regarding the experiments, and Section 5.4 presents a quantitative analysis of the generated viewpoints in regards to image quality. In the publication [8], we tested the algorithm further in simulation, showing the autonomous exploration of a shipwreck and an underwater cave environment, demonstrating that the algorithm is able to cope with a huge variety of irregular geometries.

7.5 Success rates

Table 7.1 summarizes the success rates of the results obtained throughout this thesis and describes the common causes of failure for the different algorithms and scenarios. A total of 33 experiments have been conducted throughout this thesis, in over 15 complete days of sea experiments.

Algorithm	Environment	Success rate	Failure causes
2D exploration, first version (Ch. 2 & 3)	Breakwater blocks	3/5	-Sensor noise -Navigation drift -Invalid viewpoints
2D exploration, improved version (Ch. 4)	Breakwater blocks	3/6	-Navigation drift -Strong waves
	Punta del Molar	3/4	-Rock not really 2D
	Amarrador	3/4	-Distracted by the second rock
Motion planning (Ch. 5)	Breakwater blocks	4/4	
3D exploration (Ch. 6)	Harbor	2/3	-Noise because of the water surface
	Breakwater blocks	3/3	
	Amarrador	3/4	-Sensor noise -Navigation drift

Table 7.1: This table analyzes the success rate of the different versions of the proposed algorithm.

Unsuccessful experiments due to incorrect user configuration, bugs in the software, and unrelated safety issues have been ignored to compute the reported success rates. The most common failure causes are excessive navigation drift and sensor noise.

8 Conclusions and Future Work

This chapter closes this thesis by presenting the main conclusions in Section 8.1 and proposing some research lines for future work in Section 8.2.

8.1 Conclusions

This thesis has contributed in **advancing the state of the art in underwater exploration by providing a novel multisensor online 3D view planning algorithm**. Furthermore, this thesis has contributed in **advancing the state of the art in motion planning by providing a novel multilayered start to goal planner** that accounts for the nonlinear dynamics of the vehicle and the presence of water currents.

We can break down this general contribution into more particular ones that have been achieved along the roadmap of the thesis:

Multisensor exploration We have proposed a multisensor framework that accounts for sonar and optical data simultaneously. Viewpoints are generated for each sensor, and a cost function automatically selects the best viewpoint. It is a scalable approach which has enabled us to account for multiple cameras, and would work as well in the case of multiple sonar sensors.

Octree as a core component This work has also proposed the use of multiple octrees to store the generated map, enabling isolated queries for each cell label, which are useful in the viewpoint generation process.

A set of suitable cell labels A careful selection of the cell labels has been made. Simulations and experiments have been key to determine the strengths and weaknesses of the algorithm, and that information has helped us to propose a set of cell labels that allows for an efficient viewpoint exploration algorithm.

Noise rejection A noise rejection strategy has been proposed to filter false negative sonar measurements. By using the proposed noise filtering strategy, the map coherency is improved, as it avoids generating empty regions behind the detected obstacles. It has proved to be a key element to obtain better maps to generate better viewpoints. In this work, the noise filtering strategy has been tested with a scanning profiling sonar and with a multibeam sonar, but it could be used successfully in other systems.

Deterministic viewpoint generation A deterministic viewpoint generation process has been proposed, which has been designed around the efficient operations provided by the octree data structure. This means that the generated viewpoint is only dependent on the state of the map, in contrast to other algorithms based on randomness in the viewpoint generation process. Having a deterministic viewpoint generation process is an advantage when predicting and analyzing the behavior of the algorithm under different circumstances. This deterministic model has allowed to achieve the exploration of the proposed scenarios with a limited computational budget.

Adaptability The algorithm can be easily adapted to other sensor configurations, as only their FOV and their relative position and orientation with respect to the robot are required. Regarding the software design, each component of the proposed exploration solution has been decoupled from each other, and they are easy to integrate with other software architectures.

Start to goal motion planning To improve the path planning capabilities of the exploration framework, we have proposed a start to goal motion planner that accounts for the vehicle's nonlinear dynamics and the water currents. To achieve the performance required for online planning, we have proposed a multilayered planning solution, combining for the first time ever the RRT* motion planner with the SST motion planner, in a loosely coupled architecture.

Extensive experimental validation The proposed exploration framework has been extensively validated using 2 different robots and 2 different sonar sensors. Both simulations and real experiments have been carried out in different scenarios, including man-made structures and natural environments.

8.2 Future work

This thesis has not fully solved the underwater robotic exploration problem, and there are many lines of research to explore in the future. This section discusses potential future work to further develop the algorithm presented in this thesis.

- This thesis has developed a motion planning algorithm and an exploration algorithm, but they have been tested in isolation. The next step in this regard is to integrate the proposed multilayered motion planning inside the exploration algorithm. To account for the perturbations that cannot be modeled and to add an extra layer of safety, a reactive behavior could be added to ensure the robot stays away from the obstacles and potential hazards.

- The motion planner developed in this thesis is able to take into account water currents. However, water currents are difficult to estimate during an online mission. We would like to develop a current estimation framework that would model the water currents during the exploration mission, so that the planner can account for them automatically.

- In the work developed in this thesis it has been assumed that there is no live image streaming from the cameras, so only their FOV has been used for planning purposes. However, if the cameras are connected to the computer and images are available online, we propose to process online the gathered images in order to incorporate image quality metrics to the VP algorithm.

- Regarding start to goal motion planning, it would be great to study and measure the performance of other combinations of motion planners in the proposed multilayered scheme. For instance, it would be worth exploring the use of graph-based planners, such as A*, and even optimization planners, such as [32], [33], [34] and [35]. Incorporating also the dead reckoning uncertainty in the planning would be beneficial to obtain a more reliable measure of the likelihood of collision.

- The map used in the exploration algorithm is able to filter the noise in the sonar sensor using the hit and miss approach, but it does not model properly the uncertainties in the sonar and navigation sensors. The algorithm would benefit from a more accurate treatment of the different uncertainties present in the system. In this regard, some information-theoretic references could be helpful to incorporate probabilistic approaches to the presented algorithm. Information-theoretic approaches focus on the probabilistic treatment of the information gain and mutual information to select new targets for exploration. For instance, [26], [27], [28] and [29] apply these approaches to robotic exploration and mapping. It is important to notice that the proposed map representation is already compatible with these methods, as detailed in Section 7.2 and the Appendix A.

- An idea that is worth exploring is to plan over a map represented in robot coordinates instead of world coordinates, with all the uncertainties relative to the robot. This would be useful when revisiting parts of the map that have not been observed for some time, as the new measurements give updated information about the relative distance between the robot and the obstacles, while the old measurements in the world frame have been corrupted by the robot localization drift.

- Another interesting idea is to adapt the exploration algorithm to account for a limited budget of energy or time. Having a limited budget should modify the exploration behavior, so that the robot decisions maximize the exploration while accounting for the remaining budget.

- The proposed algorithm generates the viewpoints deterministically from the frontier cells. In the majority of the cases, the proposed algorithm generates viewpoints that have 50% of overlap, as the viewpoint covers a region which is half known and half undiscovered. It would be great to explore the possibility of expanding the algorithm so that the overlap could be configured by the user.

- Unfortunately, the performance of the algorithm is affected by the localization drift. If the localization drifts, the map is no longer consistent and artifacts appear. This can decrease the performance of the algorithm, as the exploration algorithm might take suboptimal decisions due to those artifacts. To avoid the localization drift that corrupts the generated map, a simultaneous localization and mapping (SLAM) solution should be integrated. The SLAM algorithm would be able to keep the drift bounded by closing loops when revisiting locations. However, new constraints should be added in the VP algorithm to promote loop closures. In the literature this concept is usually identified as perception-driven navigation.

- It would be interesting to expand the algorithm to allow multirobot exploration. This is of particular interest when each of the robots have different sensing and maneuvering capabilities.

- This thesis has provided extensive experimentation and evaluation using the robots of the lab. However, the Boreas shipwreck and underwater caves scenarios have been used only for simulations. Performing real exploration experiments in those environments is the next step regarding field testing.

A

Entropy-based results

This section studies and compares the differences between the algorithm developed in the publications of this thesis, based on the selection of the nearest viewpoint, and an information-theoretic approach directly derived from the presented algorithm.
Since this work has focused on simultaneous exploration using two different kinds of sensors, the following approach has been used to introduce the concept of entropy in the viewpoint selection process, obtaining therefore a new approach suitable for the comparison:

1. For the k-nearest range viewpoints, generated using the deterministic approach presented in this work, the potential entropy reduction resulting from the observation of each viewpoint is computed. Instead of selecting the nearest viewpoint, the one with the greatest potential entropy reduction is selected.

2. For the camera viewpoints the same approach is followed: for the k-nearest deterministically generated camera viewpoints, the potential entropy reduction of each viewpoint is computed, and the algorithm selects the one that can lead to the maximum entropy reduction of the map. The cells that have not been viewed contribute with an entropy of 1, while viewed cells contribute with an entropy of 0.

3. Finally, between the two best viewpoints according to the entropy reduction, the closest viewpoint to the robot is selected.

Figures A.1 and A.2 show the obtained results. For the reported results, at each algorithm iteration, the nearest 100 viewpoints have been evaluated. A total of ten different simulated 3D experiments of one hour each have been made, exploring the Amarrador underwater boulder. Five experiments were conducted using the shortest distance viewpoint selection, as described throughout the different publications of this thesis, and the other five experiments used the aforementioned approach which accounts for the entropy reduction in the map for each nearby viewpoint. Results show that the entropy-based approach tends to explore the environment faster, both regarding occupancy and optical data. At the same time, however, although entropy-based exploration tends to explore faster, many small gaps are left along the way, which need to be explored at the end of the mission. Therefore, both approaches have its advantages and disadvantages, and which one is better depends on the application and required data post-processing.

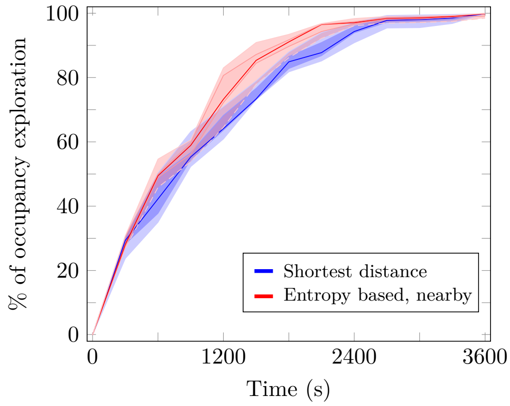

Figure A.1: Percentage of occupancy exploration as time increases. Comparison between two viewpoint selection strategies: the shortest distance approach, and the entropy-based approach among the nearest viewpoints. The entropy-based approach has a tendency to explore faster.

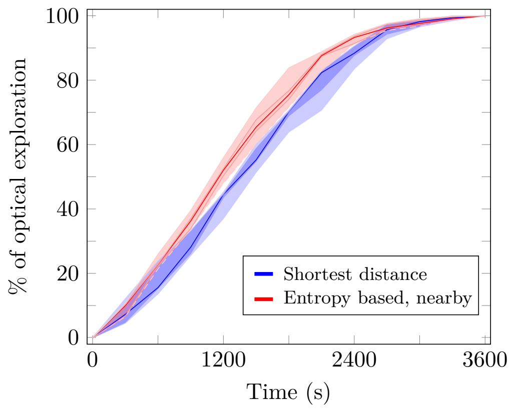

Figure A.2: Same comparison as in Figure A.1, but this time comparing the optical exploration. The entropy-based approach has also a tendency to visually explore the environment faster than the shortest distance approach.

This section has focused on comparing two different flavors of the same algorithm, to see the impact of taking into account the entropy reduction in the map when selecting the next best viewpoint for exploration. However, since the algorithm deals with multiple sensors, it is not clear which is the best way to account for the different measurements in an information-theoretic framework. This is something to be studied in future work.

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