A Processing Pipeline for Descriptive Underwater 3D Occupancy Mapping with Scanning Sonar

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Fig. 1: At left, a photo of Stevens Institute of Technology's VideoRay Pro4 System, equipped with Micron sonar and MicronNav positioning system. At right, operations at the U.S. Merchant Marine Academy in Kings Point, NY, where the data shown in this paper was gathered.

I. INTRODUCTION

We discuss an approach for 3D mapping using a remotely-operated vehicle (ROV) in cluttered shallow-water environments where port and harbor infrastructure inspection is of interest. Our goal is to equip the ROV with a mapping method that will support sound decision-making in the process of autonomously exploring a *a priori* unknown environment with a scanning sonar. This capability will be important in the initial phases of inspecting an unstructured environment, in which obtaining situational awareness, to an extent that permits reasoning about obstacles and collision avoidance, is an important first step prior to the detailed inspection of specific areas. One of the most challenging aspects of this task is producing a descriptive map amidst the high levels of noise present in the sonar data.

High-accuracy underwater sonar-based mapping has been achieved using variants of the iterative closest point (ICP) scan-matching algorithm [8], which have been applied in port and harbor settings to produce comprehensive 3D point clouds [1], [5]. In addition, particle filters have been applied [7] to produce 3D occupancy grid maps in settings with substantial supporting structure, such as underwater caves [3] and cisterns [10]. For 3D reasoning about maneuvering and obstacle avoidance, an accurate grid-based map is highly valuable. It is our goal to produce such maps in the unstructured environments in which scan-matching has previously succeeded in producing high-quality point cloud maps. To do so, we will leverage recent work in 3D occupancy mapping [9] that allows predictive inference to be performed over sparse and noisy data, producing a map that will serve as a more descriptive decision-making aid. The processing pipeline that supports this approach is described below.

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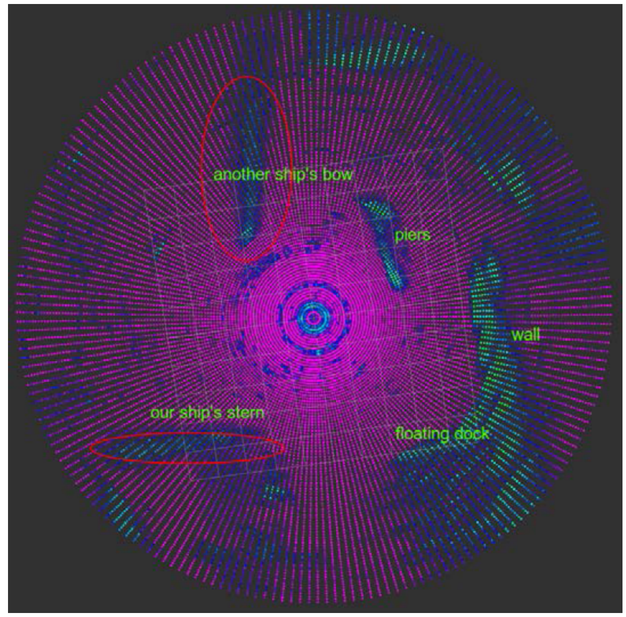


Fig. 2: An underwater sonar scan collected in a cluttered portion of a marina, in close proximity to ships, piers, and a seawall. Structures of interest are labeled.

The proposed methodology is implemented using the VideoRay Pro4 ROV, equipped with a Tritech Micron scanning sonar, shown in Figure 1. The system and its mapping pipeline have been tested at the U.S. Merchant Marine Academy in King's Point, NY, where the ROV was deployed and operated from the T/V King's Pointer, and used to map the surrounding structures in close proximity to this ship. Our base of operations is shown in Figure 1, and an example scan gathered in this environment is depicted in Figure 2.

II. SONAR PROCESSING PIPELINE

A preliminary filtering step is applied to each sonar scan to extract the points from the image that are likely to represent range returns from structures. A conservatively high amplitude threshold is applied to the entire image. The resulting points are subsequently clustered using the density-based spatial clustering of applications with noise (DBSCAN) algorithm [2], for which an appropriate number of clusters is designated automatically. Each cluster is then filtered individually using an amplitude threshold selected locally from the distribution of amplitude values within each cluster. A representative outcome of these steps is depicted

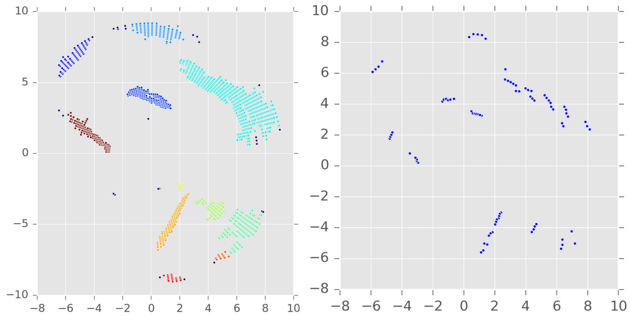


Fig. 3: At left, the contents of a single sonar scan after conservatively applied global thresholding, which is subsequently partitioned using DBSCAN clustering. At right, the results of filtering the scan cluster by cluster.

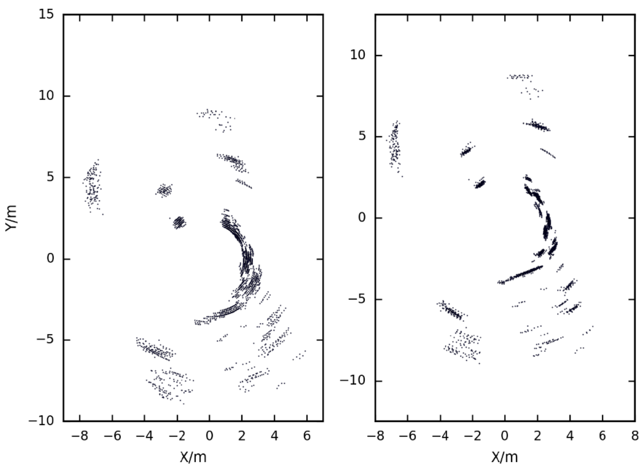
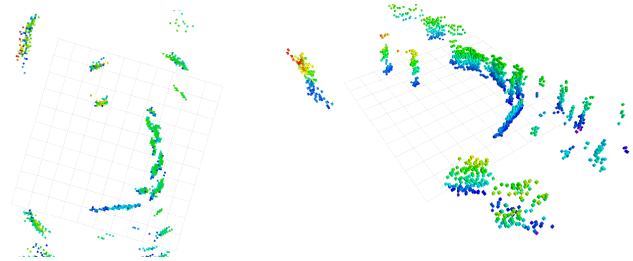


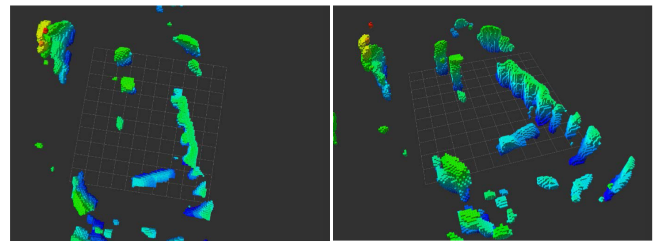
Fig. 4: At left, an overlay of scans collected while the ROV executes a depth-varying transect, assuming that the ROV's position in the plane remains fixed. At right, the resulting point cloud after the application of ICP scan-matching. The data represents the same scene depicted in Figure 2.

in Figure 3. Individual scans filtered in this manner are assembled into a composite point cloud, and consecutive scans are registered using a variant of the ICP algorithm [6]. We assume that the robot holds a fixed translational position during the collection of each individual scan, and any rotation that occurs during scanning is corrected using the ROV's compass. A depth sensor is used in concert with ICP to estimate the robot's motion between scans, ensuring accurate registration of all points in the aggregate point cloud relative to the robot's starting position. Representative results of ICP scan-matching are shown in Figure 4.

The resulting point cloud is then used to populate a 3D occupancy map. Representative results are shown in Figure 5. A standard OctoMap [4] remains quite sparse, containing many gaps that pose challenges for reasoning about motion planning and collision avoidance. However, a Gaussian process occupancy map [9] leverages predictive inference to close many of the surrounding obstacles and produce a 3D map that may serve as a tool for further decision-making about exploring this environment. The sonar-derived point cloud is used as training data for a Gaussian process regression in which the occupancy of the full map contents is predicted. Furthermore, this procedure may be implemented incrementally, scan-by-scan, in real-time.



(a) 3D OctoMap.



(b) 3D Gaussian process occupancy map.

Fig. 5: The point cloud depicted in Figure 4 is used to populate 3D occupancy grid maps. At top, an OctoMap is depicted from two perspectives. At bottom, a Gaussian process occupancy map is depicted from the same two perspectives.

Future work entails the rigorous testing and validation of the full processing pipeline in a diversity of cluttered 3D environments, and the implementation of a sequential decision-making process for the autonomous exploration of such environments. One of the key challenges in producing an accurate map is the slow rate at which the sonar's mechanical scanning beam rotates, allowing for motion of the robot in the course of collecting a sonar scan. We will explore registration of smaller scan sectors, in addition to the integration of the filtering and scan-matching process into a simultaneous localization and mapping (SLAM) framework makes corrections to the robot's trajectory across multiple time-scales. In concert with the application of machine learning to recover more descriptive occupancy maps, these processes may be used to extract the maximum benefit from the sparse, noisy sonar data that robots in cluttered marine environments must rely on.

Acknowledgments

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