3D-Surface Reconstruction for Partially Submerged Marine Structures Using an Autonomous Surface Vehicle

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***Abstract*— Over the last eight years, significant scientific effort has been dedicated on the problem of 3-D surface reconstruction for structural systems. However, the critical area of marine structures remains insufficiently studied. The research presented here focuses on the problem of 3-D surface reconstruction in the marine environment. This work is an extension of our previous approach, in which a surface vehicle that was equipped with a powerful laser scanner was designed and used to scan the above-water part of the marine structure of interest. Here we propose the design of a novel surface vehicle that is capable of using laser scanners and a side-looking sonar to scan marine structures both above and below the waterline. We also study the issue of downsampling the dataset in order to perform efficient surface reconstruction of the considered 3-D geometry, and we present a methodology for combining and integrating data from the above- and below-water parts of the structure. To illustrate the proposed robotic platform and validate our algorithms, we present results from a set of experiments in the Singapore Sea. Specifically, we present 2 different maps: the above-water map and the combined above- and below-water map. In both cases, we have two different maps: a lower quality map, that can be generated on-line, and a higher quality map that is generated off-line. To the best of our knowledge, our work is the only one that provides a 3-D model for both above- and below-water parts of marine structures. In this work we assumed a GPS-denied environment, without using any other navigation sensor such as DVL or INS.**

I. Introduction

A. Motivation

Marine structure surface reconstruction is an important problem with several applications in marine environments, including marine vehicle navigation, marine environment inspection, and harbor patrol and monitoring. A marine structure is defined as a structure that is fully or partially submerged in the sea. In this particular paper we are interested in partially submerged structures.

Recent accidents in marine areas, which have resulted in huge environmental damage (e.g. The recent Gulf of Mexico British Petroleum accident Fig. (1)), remind us that measures should be taken to efficiently inspect marine structures in order to ensure their functionality. In addition, the frequency of international terrorist attacks has increased, and marine structures are easy targets because of their size and importance. Therefore, it is necessary to develop an efficient way of inspecting marine structures in order to identify damage to, or mine-like objects attached to, them.

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Fig. 1. The recent Gulf of Mexico British Petroleum accident.

Currently, inspection of marine structures is performed by human workers through visual observation. They approach the upper part of the structures aboard small boats, and use diving equipment to approach the submerged portions of structures. In both situations, workers lack the time and the comfort to inspect the structures properly. In addition, visual examination does not give inspectors the ability to track important structural changes.

The long-term goal of this research is to develop a system capable of autonomously inspecting marine structures and monitoring marine environments. This paper presents first steps in this direction, including the perception part of the problem and the design of the vehicle. We propose the design of a novel surface vehicle, equipped with sensors such as laser scanners and sonars, that can be used to scan both the above- and below-water parts of the marine structure of interest. Experimental results, presented below, validate this concept and vehicle design.

B. Previous Work

The 3-D surface reconstruction problem has attracted substantial research interest over the last eight years. Two different types of sensors (visual sensors and laser sensors) have been used, and each type has strengths and weaknesses. Visual sensors are less expensive, but they do not provide data in $\mathbb{R}^3$. However, by using machine learning techniques or vehicle motion, this method can obtain 3D data, making reconstruction feasible [19]. Currently, vision-based surface reconstruction can be mainly accomplished in indoor environments where the distances are small and the brightness is limited.

The surface reconstruction problem can be considered a special category of the Simultaneous Localization and Mapping (SLAM) problem [11]. The traditional way of dealing with the surface reconstruction problem within the SLAM framework is to use laser scanners, which directly give points in $\mathbb{R}^3$ and work well in large bright environments (outdoors).

Although 3-D surface reconstruction by marine robots has not been done sufficiently due to its difficulty, comparable processes have been researched using ground robots. In the early stages of large-scale outdoor mapping research, 3-D data was gathered by mounting a 2-D laser scanner on a segway® [13]. In later research, vehicles were capable of directly gathering 3-D point clouds by coupling a 2-D laser scanner with a low cost nodding actuator [2], [10], or by using a 2-D spinning laser scanner [7],[6]. In most cases, advanced SLAM techniques such as features extraction, loop closures, and registration algorithms were used to attack the surface reconstruction problem.

What little research has been done on surface reconstruction by marine robots deals exclusively with underwater surfaces [17],[18],[8],[12],[14]. Currently there is no sufficient work done on surface reconstruction of both above- and below-water parts of marine structures.

In our previous contributions, we have aimed to use a surface vehicle to scan only the above-part of the marine structure of interest [15]. In the present paper, we investigate the problem of 3-D surface reconstruction for both the above- and below-water parts of marine structures. We expand our previous vehicle design into a novel surface vehicle that is equipped with sensors such as laser scanners and sonars, which are used to scan the structure. We also present a methodology for combining and integrating data from the above- and below-water parts of the structure.

The closest work to that presented in this paper is Leedekerken's recent work [16]. In Leedekerken's work, a set of 2-D laser scanners is combined with a high-accuracy localization unit that combines GPS-IMU and DVL. In contrast, our work uses a powerful LiDAR Velodyne® laser scanner and assumes a GPS-denied environment without using any other localization sensors such as IMU or DVL. In addition, Leedekerken uses a forward-looking sonar that provides bathymetry data but does not provide data on the submerged part of the structure, whereas we scan the below-water part of the marine structure of interest with a side-looking sonar. To the best of our knowledge, our work is the only one that provides a 3-D model for both above- and below-water parts of marine structures.

In the next section, section II, we describe the challenges of the marine environments. In section III, we describe the vehicle and the sensors used in the experiments. Section IV explains our localization and surface reconstruction algorithm. In section V, we provide our surface reconstruction experimental results, and we close with some conclusions.

II. The Challenge of Ocean Environment

The 3-D surface reconstruction problem has been partially solved for ground vehicles; however, the problem remains extremely difficult for marine vehicles. The marine environment is one of the most challenging environments in which a vehicle can navigate due to unpredictable disturbances such as large water currents, as well as other sources of measurement noise. Water currents, in particular, can generate disturbance forces on the kayak that result in big roll and pitch angles that make control, navigation, and perception very difficult.

Fig. (2) shows the water currents' velocity field as predicted and measured in one of our previous joint works with the Tropical Marine Science Institute of Singapore (TMSI). This field is not uniform, and features current velocities up to 100% of vehicle's maximum speed acting in different directions.

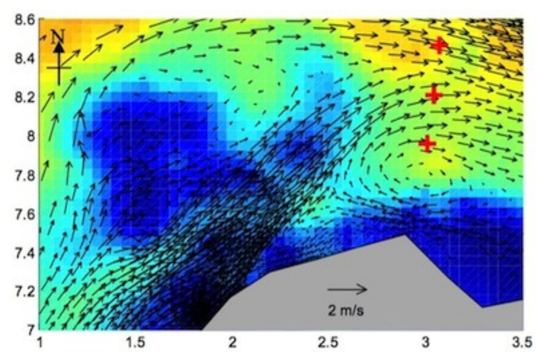


Fig. 2. Water currents' velocity field as predicted and measured in one of our previous joint works with the Tropical Marine Science Institute of Singapore (TMSI).

III. Proposed Robotic Platform

Our goal is to generate 3-D models for marine structures. Given the complexity of the marine environment, we would like to use a small but powerful vehicle with high maneuverability that will be able to access hidden places of the structure without crashing into the structure (due to water currents). For this purpose, we use a SCOUT Autonomous Surface Vehicle (ASV) – a kayak with a 3m length, 0.5m width, and 90kg mass. The ASV is equipped with a 245N thruster for propulsion, as well as a steering servo [9] Fig.(3,a).

(a) (b) (c)

Fig. 3. (a) The ASV with Velodyne LiDAR mounted on top of it. An additional pontoon is attached to the ASV to improve stability of the ASV. (b) The Velodyne LiDAR and the mounting platform for placing the LiDAR in an inverted configuration on the ASV. (c) The BlueView MB2250 micro-bathymetry sonar mounted in a sideways configuration.

No localization sensors such as GPS, INS, or DVL are used in the current paper, but the vehicle is nevertheless equipped with a GPS (Garmin GPS-18) and a compass (Ocean Server OS5000) so that, in the future, it will be able to expand our current work in all possible directions. To facilitate data capturing and autonomous control capability, the main compartment of the ASV is equipped with a Main Vehicle Computer (MVC). The MVC consists of a pair of single-board computers connected through an Ethernet cable. Each single-board computer is equipped with 1GB RAM. In addition, one of the single-board computers is equipped with a 120GB hard drive to facilitate large data capturing capability. The ASV can be controlled remotely using a remote control or autonomously using the well-known autonomy software MOOS [20],[3].

Registration algorithms frequently fail because the two point clouds to be combined have no common features. Given that our goal is to perform surface reconstruction without using any navigation sensors, we use a laser scanner with a wide field of view that allows significant overlap between subsequent scans. In addition, use a laser scanner that completes a scanning action much faster than the vehicle motion, so that we do not need to incorporate vehicle motion within a single scan. This makes the procedure simpler and reduces the computational cost of the algorithm. One sensor that meets the desired specifications is the Velodyne HDL-64E S2 shown in Fig. (3,b) mounted on the Kayak in inverse configuration. The Velodyne HDL-64E S2 is a 3-D LiDAR (Light Detection and Ranging) completes each scanning action in 0.1 second (scanning frequency =10 Hz).

The Velodyne LiDAR was initially developed for the 2007 Urban DARPA Grand Challenge. Its original configuration was supposed to be mounted on the roof of the cars to perform scanning actions in which the a full 360-degree horizontal picture with vertical arc of 26.80^o (from 2^o to -24.80^o) is captured. The Velodyne is mounted on the kayak in inverse configuration to maximize the scanning surface. To reduce of the amplitude of the rolling motion caused by the marine environment, we installed pontoons (see Fig. (3,a)).

To scan the below-water part of the marine structure of interest, we use a 3-D Micro-bathymetry sonar (BlueView MB2250 micro-bathymetry sonar). The MB2250-45 sonar uses 256 beams with one degree beam width in the elevation. Since we are interested in mapping marine structures, instead of mounting the sonar in a forward-looking configuration such as [16], we mount it sideways on the vehicle (Fig.(3,c)).

IV. Mapping

The goal of this paper is to illustrate that a 3-D model of a real marine structure in a sea environment can be constructed through the use of a single LiDAR without using any other scanning or navigation sensor. Since this work is the first to be done on surface reconstruction of marine structures that are partially submerged, we want to keep things simple; thus, we do not use advanced techniques like feature extraction and loop closures.

Based on the vehicle design described in the previous section, we propose an algorithm to construct the 3-D model of partially submerged marine structures. We use scan matching techniques to construct the 3-D model for above-water part. We then use the transformations, computed by the scan matching algorithm for the above-water part, to construct the 3-D model from a sequence of 2-D sonar data from the below-water part. We then combine the 3-D model of above- and below-water parts to construct a complete 3-D model of the partially submerged marine structure.

We construct two type of maps: a low quality and a high quality map. The low quality map can be constructed on-line and would be useful for navigation purposes. The high quality map is constructed off-line and can be used for inspection purposes.

A. Registration Algorithm

To scan a marine structure, the vehicle is driven about the structure of interest, gathering 3-D laser data. The data is logged and saved in the ASV's computer in data structures called point clouds. Each point cloud represents a set of points in $\mathbb{R}^3$ gathered by a complete 360^o rotation of the LiDAR. Since the scanning action is performed much faster than vehicle's speed, all points within a point cloud are expressed within a common orthogonal reference frame that is aligned on the center of the LiDAR at the starting point of the scanning cycle.

Given 2 point clouds M_i in $\mathbb{R}^{M\times 3}$ and M_j in $\mathbb{R}^{D\times 3}$ that include common features, we need to compute the transformation ${}^iT_j$ that transforms each point m_k of M_i to each point d_l of M_j. This problem was originally proposed and solved by Besl & McKay in 1992 using the ICP algorithm [5], by minimizing the following metric:

$$E({}^iR_j, {}^ib_j) = \sum_{k=1}^{M}\sum_{l=1}^{D}(w_{k,k}||m_k - ({}^iR_j d_l + {}^i b_j)||^2) \quad (1)$$

Here, $w_{i,j}$ is a binary variable as follows: $w_{i,j}$=1 if m_i is the closest point to d_j within a close limit and is equal to zero otherwise. ${}^iR_j$ and ${}^ib_j$ are the rotation matrix and the translation vector defined in [21].

B. Above-Water Surface Reconstruction Algorithm

The vehicle gathers point clouds $(M_1, M_2...M_{n-1}, M_n)$ with frequency of 10 Hz. We sequentially merge these 3-D point clouds, each in their respective coordinate systems, into a single coordinate system. The transformations between sequential point clouds $({}^0T_1, {}^1T_2..., {}^{n-2}T_{n-1}, {}^{n-1}T_n)$ is given by the ICP algorithm described in the above section. The first point cloud in the sequence is transformed into the coordinate system of the second point cloud. The union of the first two point clouds is then transformed into the coordinate system of the third point cloud, and so on. This process continues until we transform all the point clouds into the coordinate system of the last point cloud in the sequence.

The Velodyne LiDAR generates around 8 MB of data per second (250,000 points per scanning cycle and 10 scanning cycles per second). The computational cost and memory requirements to deal with this amount of data are huge, making ICP impossible to run on-line. The time for a single merging process in the worst case is $O(NlogN)$ where N is the number of points in the current map. This complexity is dominated by searching for correspondence points. For online-mapping, we speed up the search process by using the ASV maximum speed to bound the maximum possible displacement d, and hence limit our search space. Furthermore, we fix a maximum number of possible iterations to ensure termination within the required time.

In addition, we reduce these computational demands in two other ways. First, instead of using the raw data as gathered, we use data from scanning actions performed every Δ_t seconds. Second, we perform spatial sub-sampling on each point cloud by discretizing the bounding box of the point cloud into a regular grid with user-specified resolution; thus, all the points inside a single grid cell are represented by a single point. By limiting cells to a given size (resolution), we both reduce the amount of data to a reasonable quantity and also cancel out the errors (assuming zero mean noise).

To get the on-line map, we simplify the data as described above using a large simplification cell size and large Δ_t, as shown in Fig. (4). This on-line map is a low-resolution map that can be used for for navigation.

To get a higher quality map, we want to use as much data as we can handle. To do so, we generate an occupancy grid-based map under a probabilistic framework such as OctoMap

Fig. 4. The online map: we use big simplification cell size.

[22]. Because the LiDAR generates a huge amount of data, we still use simplified data (albeit less simplified than above), rather than raw data, in order to get the transformation matrices. We then use the transformation matrices to merge the raw data, resulting a single, dense 3-D point cloud. An occupancy grid-based map is then generated using OctoMap. The resulting grid-based map is used to get the mesh of the structure using the ball-pivoting algorithm [4]. This process is shown in Fig. (5). This high-resolution map must be generated off-line, and can be used for inspection or for further analysis (depending on the application).

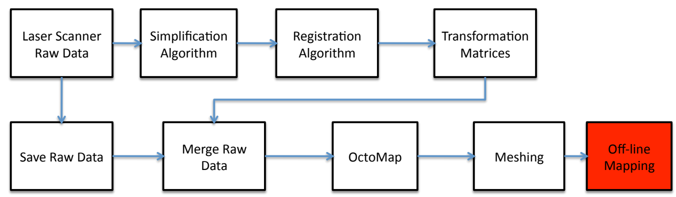


Fig. 5. The off-line map: Less simplified data are used to get vehicle's trajectory and then vehicles' trajectory is used to project raw data resulting a dense point cloud.

Two parameters effect drastically the computational cost of our method: Δ_t and cell size. A small Δ_t results in big computational costs, leaving time intervals between scans that are too small to solve the problem on-line. On the other hand, given that we are not using other localization sensors, a large Δ_t may result in the failure of the ICP algorithm, since the algorithm cannot merge point clouds gathered from sequential locations that are not sufficiently close to each other (i.e., get stuck in a local minimum).

In Fig. (6) below, we can see the trajectories that the ICP algorithm yields for different values of Δ_t $(C_1, C_2...C_5)$. We observe that trajectories corresponding to different values of Δ_t form a sequence with decreasing differences as Δ_t goes to zero (i.e., the sequence trajectories have the Cauchy property and thus there exist a limit). Therefore, for this particular dataset, the benefit of reducing Δ_t below 1 second is not worth the computational cost for either the online mapping or the offline mapping.

Regardless cell size, as long as it is small enough to capture geometrical features that are important to the ICP algorithm, it does not effect the localization. For the off-line map, simplification cell size generally does not matter, as long as the localization works properly, since we are using vehicle's trajectory to project dense raw data[1]. However, for the on-line map, the cell size is bounded by the accuracy we want to have in the map.

[1]In the offline map, the voxel size and the probability threshold given in the OctoMap algorithm are important and reflect the resolution we want to capture.

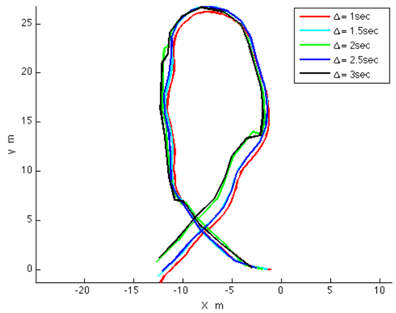


Fig. 6. Trajectories generated during the first 100 seconds of one of the experiments: Trajectories corresponding to different Δ_t form a sequence with decreasing deference.

C. Combined Map

In order to create a complete 3-D model of the entire partially submerged marine structure, we use the 3-D Micro-bathymetry sonar described in Section (III) to get the below-water part of the marine structure, and then we combine this data with the model of the above-water part of the structure. The vehicle's trajectory generated by our above-water mapping algorithm is used to register the 2-D sonar data into the global 3-D map.

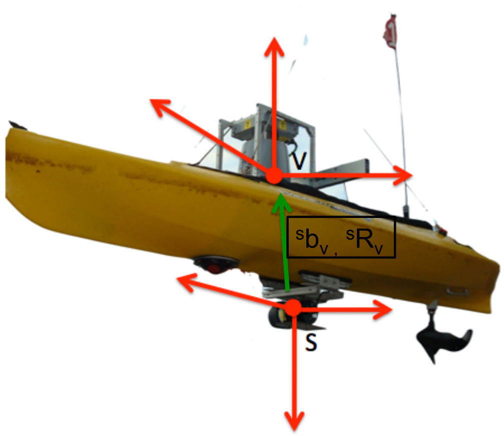


Fig. 7. The coordinate systems of LiDAR and sonar

The vehicle's sonar generates 2-D data in the polar coordinate system (r, ϕ, I), where r and ϕ are the ranges and the angles of the returns and I is the intensity (see Fig. (8)). Since we want to project 2-D sonar data into the Cartesian global coordinate frame generated by the above-water surface reconstruction algorithm, we transform the 2-D sonar data to an equivalent local Cartesian frame using the equations below:

$$^{s}x_{s} = r\cos\phi \quad (2)$$

$$^{s}z_{s} = r\sin\phi \quad (3)$$

$$^{s}y_{s} = 0 \quad (4)$$

The sonar data are then transformed into the current LiDAR coordinate system using Equation (5). This allows the sonar data to be treated and propagated as equivalent to Velodyne data as described in section (IV-B)

$$^{v}X_{s} = [^{s}T_{v}][^{s}X_{s}] \quad (5)$$

where $[^{s}T_{v}]$ is the transformation matrix from the sonar coordinate system to the Velodyne system, as shown in Fig. (7) and $^{s}X_{s} = [^{s}x_{s}, ^{s}z_{s}, ^{s}y_{s}]^{T}$. At the present time, the registration between sonar and LiDAR data is done by manually measuring the transformation from sonar frame to the LiDAR frame. In the near future, we intend to implement a registration algorithm to do the registration between LiDAR and sonar data.

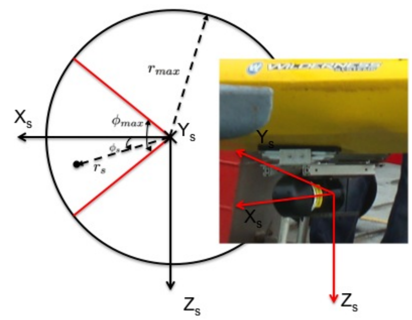


Fig. 8. Sonar coordinate system: Sonar gives returns up to 10meters with in an angle of 45 degrees

Sonar data are noisy, so to clean up the data, we extract objects from the raw sonar data using clustering filtering methods. Fig. (9) compares the raw sonar data to the data that has been cleaned using clustering filtering methods.

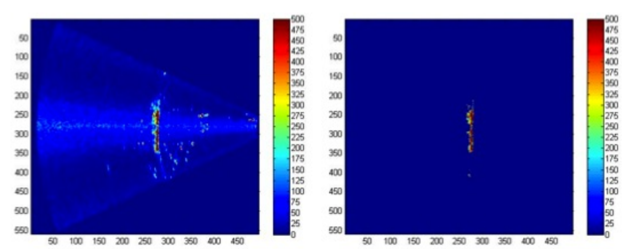


Fig. 9. Sonar data: In the left figure we can see a frame of raw sonar data, in the figure in the right we can see the filtered sonar data using a filter based on clustering.

V. Experimental Results

To evaluate our algorithms, we performed a set of experiments in the Singapore Sea in the summer of 2010. In this particular paper, we present results from tests performed with a jetty located at Pulau Hantu (a small island few kilometers away from Singapore). We deployed our vehicle from a ship near Pulau Hantu and drove it about the jetty to gather data. Results given here are post-processing results, since none of our surface reconstruction algorithms were running on-line (as illustrated in Fig. (11), if we had reduced the cell-size the surface reconstruction algorithm could have ran on-line).

Here we present two missions. The first mission lasted 3 minutes and gathered data for the above-water part of the jetty. In this mission, we drove the vehicle a distance of about 200m making sure that the vehicle approached the structure from different views to recover all the hidden parts of the structure. The second mission lasted 1 minute and gathered data from the above- and below-water parts of the floating platform that was located in front of the jetty (see Fig. (10)).

Fig. 10. The marine structure of interest.

We present 3 different maps of the jetty and the floating platform. The first map is a low-quality point cloud-based map that could be generated online and can be used for navigational purposes (Fig. (11,12)). The second map is a higher quality mesh-based map (Fig. (13,14)). The third one combines both the above- and the below-water parts of a single marine structure (Fig. (15(b),15(c))).

In Fig. (11,12) we can see the low-resolution point cloud-based maps of the the jetty for different cell sizes. We can verify that the one that was generated with 30 cm cell size can be generated on-line. For both cases $\Delta_t = 1$ second.

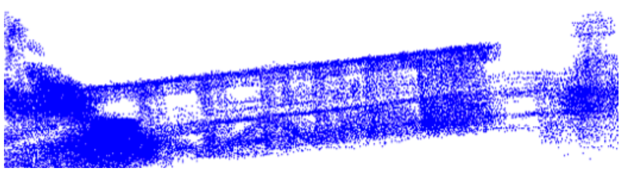


Fig. 11. Low-resolution map, cell size= 30cm, the mission lasts 3mins, is generated in 3mins (3GHz CPU).

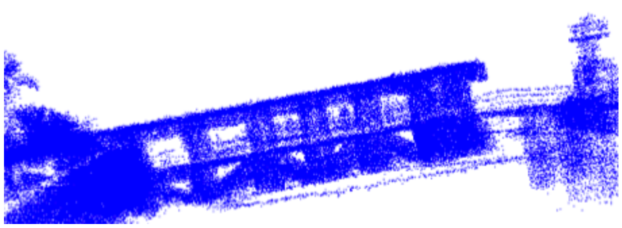
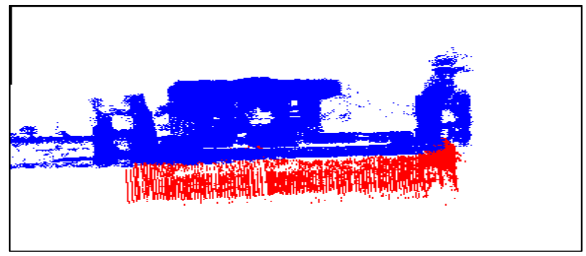


Fig. 12. Low-resolution map, cell size= 18cm, the mission lasts 3mins, is generated in 8mins (3GHz CPU).

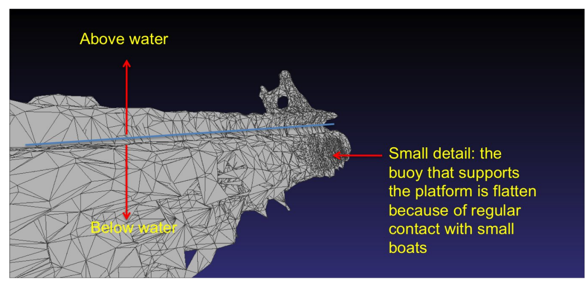
In Fig. (13,14) we present different views of the high-quality mesh-based maps of the jetty. The voxel size used in the occupancy grid generation was 10cm and Δ_t =1 second. Here we present two different high quality maps; the first one (Fig. (13)) was generated using a high probability threshold for occupied cells, and the second one (Fig. (14)) was generated using a low probability threshold for occupied cells resulting in a dense map.

Fig. (15(b)) shows the point based map for both the above- and below-water parts for the floating platform. Fig. (15(c)) shows the combined mesh based map in zoom view. We notice that the buoy that supports the floating platform is flattened due to regular contact with boats. In all cases, the mesh is generated using meshlab [1]

(a) Picture of the front part of the structure



(b) Above- and below-water parts of marine structure, point cloud-based map. In red color below water part, in blue color above water part.



(c) Above- and below-water mesh-based map: Small details.

Fig. 15. Combined map

VI. Conclusions and Future Work

In this paper, we present a solution to the 3-D surface reconstruction problem for marine structures that are partially submerged. We propose the design of a novel surface vehicle that is equipped with a Velodyne LiDAR and a Micro-bathymetry sonar used to scan the structure above and below the waterline. We also develop an algorithm for combining and merging data from the above- and below-water parts of the structure. To illustrate the proposed robotic platform and validate our algorithms, experimental results are presented from data gathered in the Singapore Sea.

The long-term goal of this research is to develop a system capable of autonomously inspecting marine structures and patrolling marine environments. In the future we aim to develop navigation techniques for autonomous inspection of marine environments.

In this work, we have assumed GPS-denied environment, without using any other navigation sensor such as DVL or INS. Of course in the long time horizon navigation in large environments, we are interested in, GPS and other navigation sensors, combined with more SLAM advanced techniques

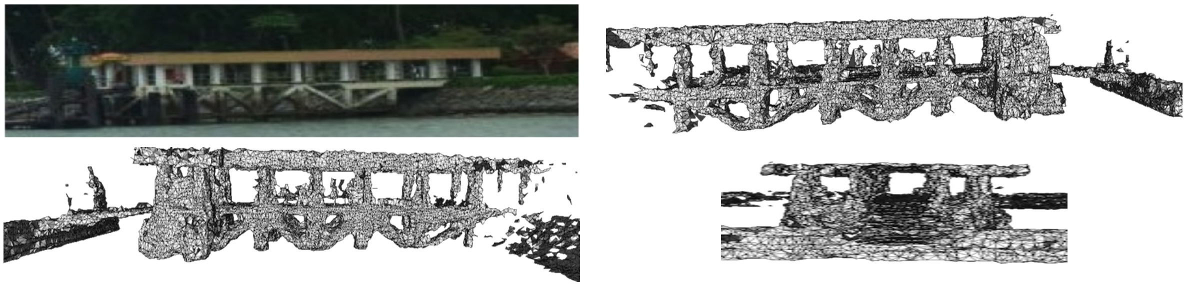


Fig. 13. The mesh-based high quality map for the above-water part of the jetty, using a high probability threshold for occupied cells.

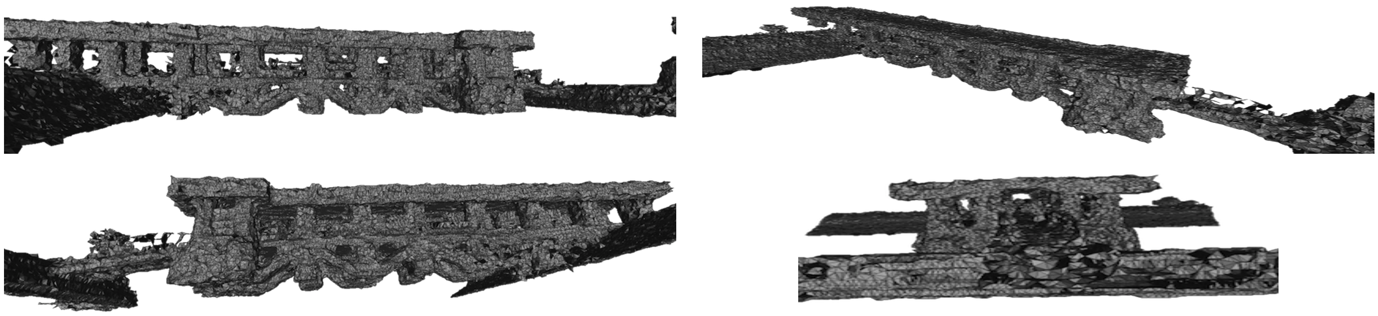


Fig. 14. The mesh-based high quality map for the above-water part of the jetty, using a low probability threshold for occupied cells.

such as feature extraction and loop closures should be used to bound localization accuracy, which crucially effects the quality of the map.

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