An Algorithm to Identify Docking Locations for Autonomous Surface Vessels from 3-D LiDAR Scans

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***Abstract*— In this paper we present a novel algorithm to identify docks (or piers) from Light Detection and Ranging (LiDAR) scans. The algorithm exploits the expected geometric features of the dock and does not require modifying the dock in any way. Our approach consists of a novel combination and application of open source tools for point cloud and image processing. In our limited testing on 8 fused data sets, the algorithm successfully identified a usable portion of all the docks with only one false positive (a seawall). The target application is automated docking (a.k.a. recovery) for small Unmanned Surface Vessels (USVs).**

Keywords—Unmanned Vehicles; LiDAR; Object Recognition

I. Introduction

The strategic vision for the Department of Defense includes an increased reliance on unmanned combat vehicles, due to their ability to reduce risk to human lives, cut costs, and maintain persistent situational awareness for extended periods of time. In particular, the US Navy's *Unmanned Surface Vessel (USV) Master Plan* [1] identifies some of these benefits, along with key operational challenges, as they apply to the maritime domain. One of the engineering issues presented in that document is the launch and recovery (L&R) of the semi-autonomous and autonomous surface vessels.

We are focused on small USVs (6-11 meters), capable of operating in harbors, bays and rivers, which may be launched from wooden piers. A prerequisite for autonomous docking (a.k.a recovery) is the ability to automatically identify and locate the docking area. In this paper we address the difficult problem of autonomously recognizing and locating unmodified docking sites (a.k.a. piers) in the field based on their size and shape.

A. LiDAR – Light Detection and Ranging

Three-dimensional LiDARs have proved themselves very useful on many autonomous ground vehicles, including nearly every entry into the DARPA Grand [2] and Urban [3] Challenges, ElRob [4] and most recently the Google Driverless Car Project. In these applications LiDARs have been used as the primary sensor to estimate the location of the roadways, curbs, obstacles and even lane markings relative to the vehicle.

In this project we use a LiDAR sensor to detect the geometric features of the dock. The decision to use a LiDAR, in spite of their relatively high cost, was based on several factors. First, unlike computer vision, LiDAR makes direct range measurements and is not sensitive to changes in the ambient lighting conditions. Second, unlike Long and Short Baseline Acoustic systems (SBL and LBL), there is no need to modify the dock or surrounding waters by adding beacons or transponders. Finally, this type of sensor is already mounted on many autonomous vehicles for obstacle avoidance purposes.

Specifically, we used Velodyne HDL-32E in this project (shown in Figure 1 –Left), principally because it is the one of the cheapest 3-D LiDAR available. This sensor consists of an array of 32 eye safe lasers arranges in a vertical plane at elevation angles ranging from -30 to 10 degrees. The gestalt spins about its vertical axis, making a full rotation every 0.1 seconds while collecting 700,000 range measurements of the surrounding area out to 100 meters with a reported error of +/-2 centimeters. It also included an embedded inertial measurement unit that can be used to estimate the sesnor's roll and pitch, as well as a small GPS. The resulting range data can be visualized as a point cloud, as seen in Figure 4 (top).

B. Dock Types

Since we are focused on small USV (6-11 meters), capable of operating in harbors, bays and rivers we chose to focus on smaller wooden piers. Clearly, these structures come in many forms. In order to make the problem tractable, for the purposes of this paper, we define a "dock" as an object satisfying three geometric criteria. It must include:

1. a horizontal planar surface at least 5 meters long and 1-2.5 meters wide,
2. that is surrounded by water on both of its long sides, and
3. is outlined by pilings – vertical cylindrical objects between 0.3 and 0.5 meters in diameter, protruding at least 1 meter above and below the horizontal surface.

Figure 2 (left) shows a canonical example of dock that fits this description. Clearly floating docks (center) or mooring points along a seawall (right) are feasible docking locations; however they are not considered in this paper.

II. Data Collection

A. Raw Data Sets

The LiDAR was mounted on large cart at the top of a 4 meter mast (shown in Figure 1 - right), similar to how it would be mounted on a USV. Data was captured from a land-based vantage point to ensure the sensor was stationary and the pitch and roll angles were close to zero. Each data set includes the latitude and longitude at which the data was captured (using a DGPS with reported accuracy of 1-2 meters), the heading of the LiDAR (using a 3 axis magnetometer with reported accuracy of 0.5 degrees), the LiDAR range data taken at that location, and a set of 4 reference photos of the surrounding area. 12 data sets were taken at our initial test site (Figure 3-top). Six more data sets were taken at a second test site (Figure 12-top). All the data sets were captured under favorable atmospheric conditions – no rain, snow or fog.

Figure 1: (left) The Velodyne HDL-32E 3-D LiDAR. (right) The LiDAR mounted on a 4 meter mast used for data collection.

Figure 2: (left) The dock type considered in this paper. (center and right) Docking locations that do not meet the criteria used in this paper.

B. Point Cloud Registration to Increase Density

One of the initial difficulties we encountered was that a single data set often resulted in a point cloud that was not dense enough to permit dock recognition. Figure 4 (top) shows a typical result. Even with 32 lasers, the difference in elevation angle between adjacent lasers is approximately 1.3 degrees. When scanning objects 30 meters away – a typical distance at which a boat captain might begin to plan a docking approach – the gap between adjacent laser returns can be anywhere between 0.7 and 3 meters. Considering that the docks are on average 2 meters wide and the pilings are approximately 0.3 meters in diameter, the resolution is clearly insufficient to discern the geometry of the dock.

One possible solution is to use a higher resolution LiDAR – Velodyne makes a 64 laser variant. Another would be to collect the data much closer to the dock. The first solution was prohibitively expensive ($64,000 USD) and the second did not reflect typical maritime operating procedures. Instead we decided to register and concatenate multiple data sets to form a more dense point cloud. Registration is the process of taking two partially overlapping datasets, estimating the homogenous transformation between them using a combination of odometery information and feature matching. The points can from the two data sets can be concatenated by spatially transforming the data from one set into the perspective of the other set (Figure 4 - bottom), forming a denser data set. We felt that this approach is resembles current maritime practices, in that the USV could be continually amassing data about its target docking location during the gross approach phase, making multiple passes if needed to assess the site.

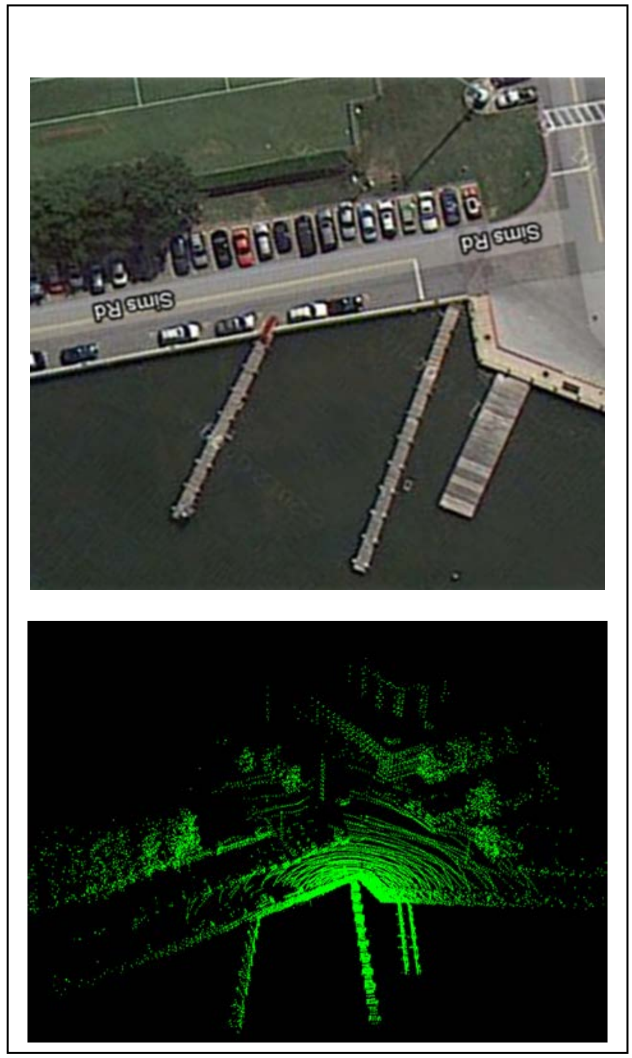

Figure 3: (top) A Google Map image of the original testing location. Note that the deck of the thick pier on the right was partially destroyed in hurricane Sandy. (bottom) A dense point cloud of the area, formed by combining three separate LiDAR scans.

We employed a two phase approach for the registration process. First, using the difference between the latitude, longitude and compass readings for the two datasets as an initial guess, a global registration method, Sample Consensus

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Initial Alignment (SAC-IA), quickly computes a rough estimate of the spatial transformation between the datasets [5]. Then, that rough estimate is used as the initial guess for the well-known local alignment method, the Iterative Closest Point (ICP) algorithm [6]. We used Point Cloud Library's (www.PCL.org) implementations of both algorithms, carefully adjusting the user-defined parameters and options. In our experience, this two part global-local approach was necessary due to the repeating geometry of the docks – long flat featureless planar surfaces, surround by repeated patterns of pilings with nearly identical spacing. When the ICP was used alone, it often incorrectly associated pilling from the two scans.

Figure 4 (bottom) shows the successful results of registering two scans (shown in red and green) using this process. Typically, 3 of the original data sets could be registered to form a sufficiently dense, or fused, scan, such as the one shown in Figure 3 (bottom). This resulted in 4 dense data sets from the first test site and 2 from the second test site.

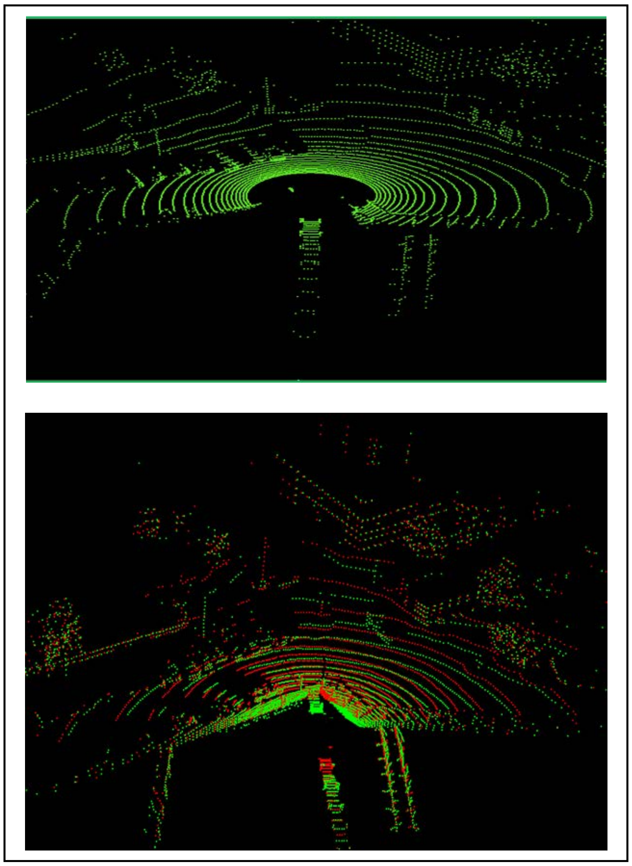

Figure 4: (top) A single LiDAR scan is not sufficiently dense to estimate the geometry of the dock. (bottom) LiDAR Scans taken from two different view-points (red and green) are registered and fused together to form a denser point cloud.

III. Algorithm

Our dock identification algorithm consisted of four steps.

1. Shore Removal
2. Horizontal Planar Surface Segmentation
3. Pilling Classification
4. Pilling to Plane Proximity and Shape Check

These steps, explained below, were implemented using tools from Point Cloud Library and Open CV (www.openCV.org) – two popular free and open source C++ libraries. The dense data set shown in Figure 3 (bottom) was used to develop the algorithm and tune the parameters.

A. Shore Removal

Because the water refracts the laser, the LiDAR does not get a return from the water's surface. For this reason, the docks resemble long thin clusters of points extending from the larger point cloud associated with the nearby shore. In this step we attempt to identify and remove the vast majority of the data points associated with the shore. This greatly reduces the number of point that need to be processed in subsequent steps.

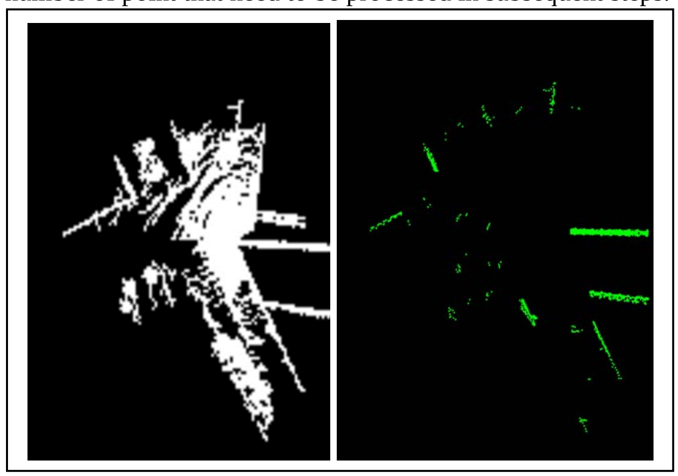

Figure 5: (left) An occupancy grid representing a bird's eye view of the area as a binary image. (right) Morphological operations are used to eliminate most of the shore.

First we use the point cloud to create a 2-D occupancy grid [7]. The result can be visualized as a binary image representing an overhead view of the scan area, as seen in Figure 5 (left).

Next we employ the morphological "opening" algorithm, implemented in OpenCV, to remove the long protrusions. An *opening* is a two part process. First we *erode* the white object, in this case by 2 meters (slightly larger than the expected width of the dock). While this operation removes the docks and similar objects completely, it also removes part of the shoreline. Therefore, we follow that operation with *dilation* by 2 meters which approximately replaces the shoreline. The remaining points are *not* dock candidates, and so they are removed from the original point cloud leaving behind the points shown in Figure 5 (right). The remaining points include the docks. Unfortunately the part of dock that is connected to the shoreline is also removed during this process. However, that part of the dock is rarely safe to dock at since it may be shallow and in close proximity to a seawall. In addition to the docks, other long thin sets of points remain. Such as the vertical walls of building on the shoreline and parts of automobiles parked along the seawall, which will be removed in the next step.

B. Horizontal Planar Surface Segmentation

In this phase we attempt to segment the part of the pier that resembles a flat horizontal walkway. The Random Sample Consensus (RANSAC) algorithm was used to estimate the best fit plane to the dataset. RANSAC is an iterative method that estimates parameters of a mathematical model (i.e. the coefficients in equation of a plane in this case) based on a randomly chosen subset of the data, containing both noisy inlier and outlier data points [8]. We used two screening criteria. First, inlier data points had to be within 0.25 meters of the best fit plane in the vertical direction. This prevents the pilings from being classified as part of the plane, while still allowing for the fact that many docks are not perfectly planar. Second, candidate planar surfaces had to have roll and pitch angles within 15 degrees of the horizontal. This eliminates nearly vertical planes such as seawalls, buildings and other boat hulls. Figure 6 shows the point cloud after the shore has been removed. The points highlighted in red are candidate horizontal planar surfaces segmented using RANSAC.

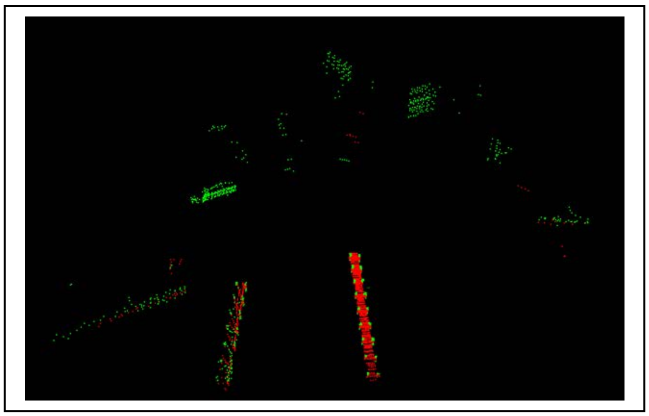

Figure 6: After the shore has been removed, RANSAC is used to identify horizontal planar surfaces (highlighted in red).

C. Pilling Classification

After the shoreline is discarded, and the points corresponding to horizontal planar surfaces are set aside the scan resembles Figure 7. Our next step is to identify possible pilings. First the Euclidian Cluster Extraction module in PCL is used to group the remaining points into clusters, by looking at the distance between nearest neighbors (<0.3 m).

Since pillings should resemble vertical cylinders, our first thought was to fit a cylinder to the data using RANSAC, however, at longer ranges, the poor resolution precluded this approach. Instead we implemented a Bayesian classifier to evaluate each cluster using the following discriminating features: 1. mean height (Z) of points in the cluster; 2. standard deviation in the X, Y and Z directions; 3. covariances (XY, YZ, XZ). We trained the algorithm on a set of 5 hand segmented point clouds (not included the original data set) containing 125 clusters— 22 of which were pilings. The close up shown in Figure 8 highlights the identified pilings in red.

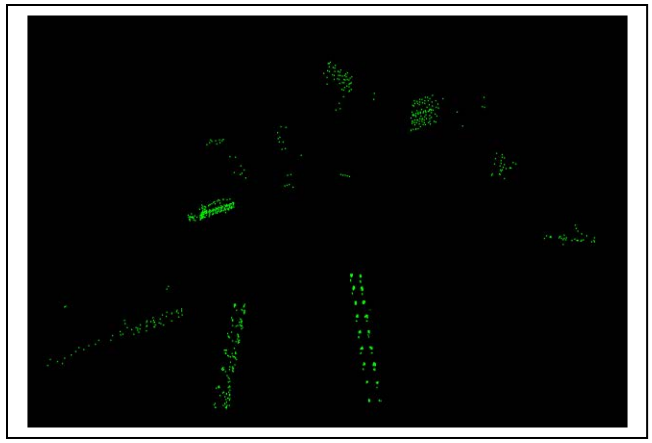

Figure 7: After removing the shore and any horizontal planar surfaces, the remaining points are grouped into clusters.

D. Pilling to Plane Proximity

With the candidate pilings and non-shoreline planar surfaces segmented, the last step to check their proximity. For this we again created occupancy grids representing bird's eye views of the scene. One grid (Figure 9 – right) includes only the horizontal planar surfaces, now dilated by 1.5 meters. The other grid (Figure 9 – left) includes only pilings identified by the Bayesian classifier. After overlaying these images, a dilated planar surface is considered a candidate dock only it they intersect with at least 3 pilings.

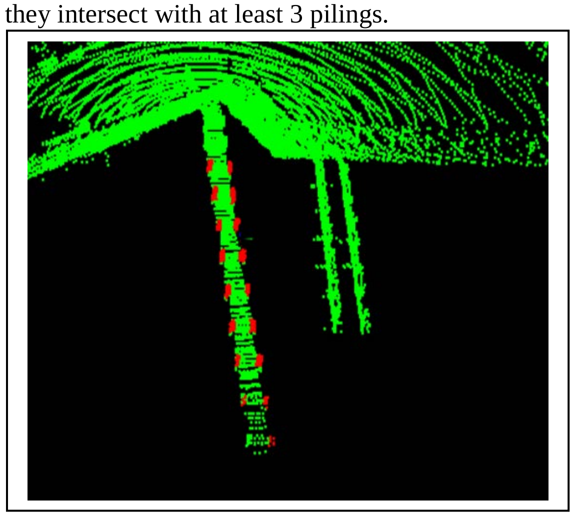

Figure 8: This close up of the point cloud shows the clusters that were identified as pilings using our Bayesian classifier (highlighted in red).

We found that, occasionally, other objects passed these tests – in particular certain segments of the seawall which are both planar and lined with posts resembling pilings. Therefore, we reject any candidate dock less than 4 meters in length or more than 3 meters in width.

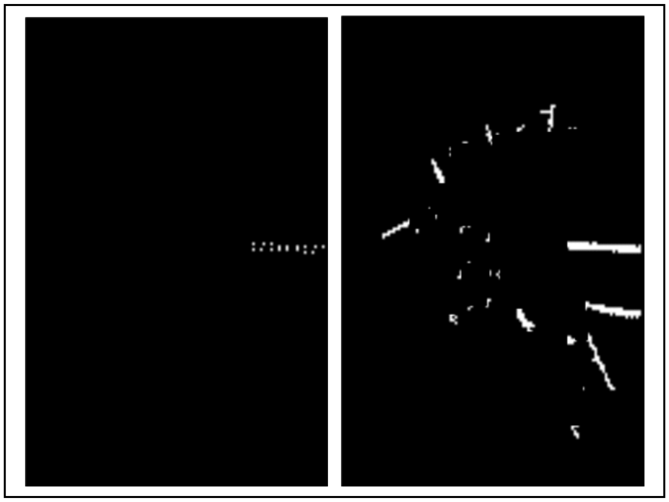

Figure 9: Using the overhead occupancy grid representation, the pilings (left) and dilated horizontal planar surfaces (right) are checked for overlap.

IV. RESULTS

After the algorithm was developed it was tested on the remaining data sets. Some example segmentations can be found in Figure 10-Figure 13. Figure 10 shows an ideal result on Dataset 1. The dock is highlighted in red, with the exception of the unnavigable part near the seawall. The damaged docks are not identified. The segmentation on Dataset 2 is similar and is not shown. Figure 11 shows the results from Dataset 3, highlighted in red. Note the false negatives at the tip and middle of the dock. The laser was positioned at a more oblique angle and the point cloud is not sufficiently dense there, causing apparent breaks in the planar surface or making the pilings difficult to find. However, the red area is still large enough that it could be used to navigate a USV into a successful docking configuration.

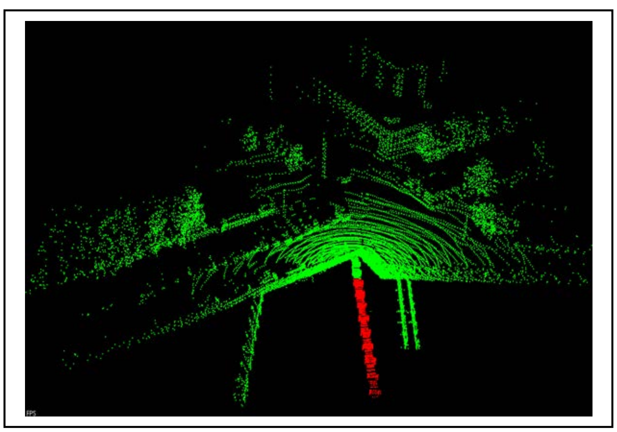

Figure 10: Using data from the scene depicted in Figure 3, the red points have been correctly identified as part of the dock. Note that the two damaged docks are not highlighted.

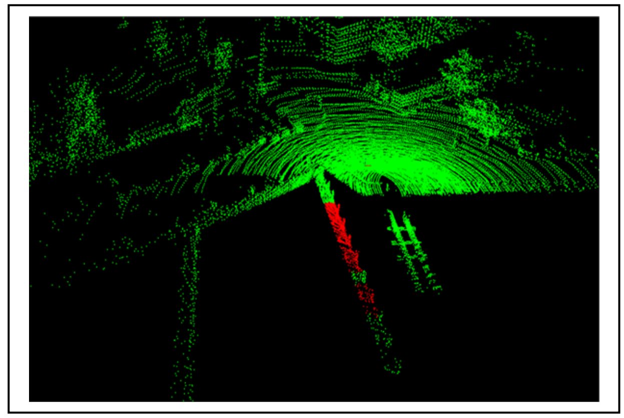

Figure 11: Using data taken from a different perspective than Figure 10, most of the dock is correctly identified (red). There are false negatives near the end where the scan is not sufficiently dense.

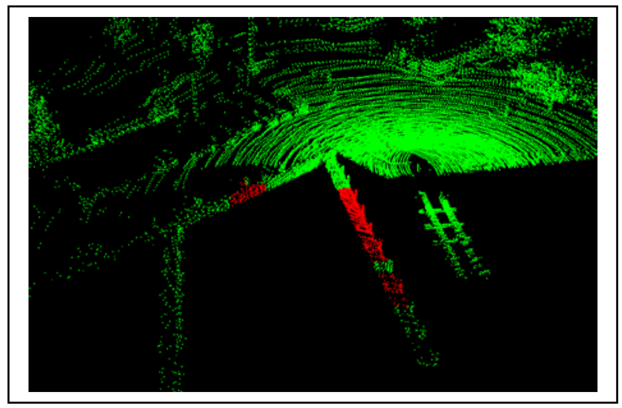

Figure 12: Using data taken from a different perspective than Figure 10, most of the dock is correctly identified (red). Note the false positive along the straight portion of the seawall longer than 4 meters.

Figure 12 shows Dataset 4, with the identified docks highlighted in red. Here there are false positives along the seawall, which is also horizontal, planar and lined with posts resembling pilings. Because it is raised, there is a shadow area behind it which is difficult to distinguish from the surrounding water. This particular segment is more than 4 meters long, so it was not removed by our minimum length filter.

Finally, Figure 13 shows a Google Map image of the second test site – Datasets 5 and 6. Note that the two docks in the lower left corner had been demolished prior to the data collection and do not appear in the point cloud. This scene includes several complex features, such as dense foliage (tree trunks resemble pilings), a boat ramp that is planar, and isolated pilings. Also, two of the docks are not rectangular. The algorithm correctly identified the dock that met our criteria along with portions of the T shaped dock that match the criteria.

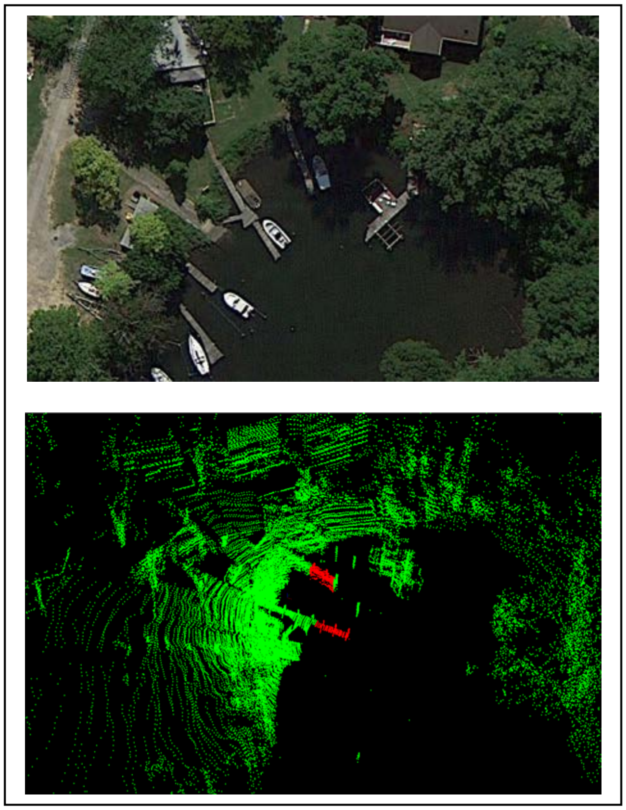

Figure 13: Point cloud data from a different test site, which includes isolated pilings, more foliage, and multiple docks – the bottom one is T-shaped. The algorithm correctly identified (red) the portions of the dock that meet our criteria.

V. Conclusions

In this paper we present a novel algorithm to identify docks (or piers) from LiDAR scans. The target application is automated docking (a.k.a. recovery) for small Unmanned Surface Vessels. The algorithm exploits the expected geometric features of the dock. It consists of a novel combination and application of open source tools for point cloud processing, image processing. In our limited testing on 6 data sets the algorithm successfully identified at least part of the docks in all cases with only one false positive.

We feel that the approach has several strengths. First, it does not require adding fiducials or active beacons of any kind to the dock site. Second, the use of LiDAR imagery means the method is invariant with respect to ambient lighting conditions, unlike computer vision approaches. Finally, the algorithm can be easily tuned to the geometry of the dock (length, width, piling size); yet all the underlying methods are robust to small variations in geometry and the presence of noisy data points.

There are a few limitations of this method. First, it requires a relatively expensive sensor (LiDAR), although these units are becoming increasingly common place on autonomous vehicles. Second, the point cloud must be sufficiently dense to identify the pilings, which can be problematic at long ranges. We mitigated this challenge by registering and concatenating successive scans. However, this process is computationally intensive. Finally, the method is limited to piers of a specific shape – namely long thin docks, surrounded by the pilings, and extending from the shore line. Floating piers, T-shaped docks, or mooring points located along a seawall would not be identified unless the algorithm was modified. At present the algorithm takes approximately 10 second to segment the dock, which may not be suitable for real-time operation, though we are confident it can be optimized further.

The most important area for future work is to test the algorithm on a wider range of data sets. Testing on a greater variety of data sets would help establish the robustness and generality of the algorithm. In particular the algorithm needs to be tested with data collected from a LiDAR mounted on a moving vessel, subject to pitch, roll and heave motions.

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