ALFA Task 2 Deliverable M2.3.1: Autonomous Mapping in Marine Renewable Energy Arrays

Geoffrey Hollinger
Oregon State University
Phone: 541-737-5906
geoff.hollinger@oregonstate.edu

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1 Introduction

This document presents results from tests to demonstrate underwater mapping capabilities of an underwater vehicle in conditions typically found in marine renewable energy arrays. These tests were performed with a tethered Seabotix vLBV300 underwater vehicle. The vehicle is equipped with an inertial navigation system (INS) based on a Gladiator Landmark 40 IMU and Teledyne Explorer Doppler Velocity Log, as well as a Gemini 720i scanning sonar acquired from Tritech. The results presented include both indoor pool and offshore deployments. The indoor pool deployments were performed on October 7, 2016 and February 3, 2017 in Corvallis, OR. The offshore deployment was performed on April 20, 2016 off the coast of Newport, OR (44.678 degrees N, 124.109 degrees W). During the mission period, the sea state varied between 3 and 4, with an average significant wave height of 1.6 m. Data was recorded from both the INS and the sonar.

During the deployments, the vehicle captured images of objects from multiple view points. In doing so, the vehicle experienced a wide range of motion (e.g. translational, rotational, and translational/rotational combinations). During the pool deployments, the vehicle primarily observed an "X" shaped object. Square, "T", and triangle shaped objects were also observed. During the offshore deployment, the vehicle observed an underwater sinker block. The data recorded from these deployments was used to reconstruct the objects in 3D for the purpose of mapping.

The rest of this report is organized as follows: Section 2 briefly describes the parameters of the data set and the associated code files that allow the user to interact with the data. Section 3 reports the results of the reconstruction experiments.

2 Data Set

The data sets used in the reconstruction experiments is comprised of two main parts: navigation data and sonar imaging data. The vehicle navigation data is presented in the vehicle's local coordinate system. Each of the data points contains the vehicle's pose and a time stamp. The vehicle's pose is represented as a position (x, y, z) in meters and an orientation (roll, pitch, yaw) in radians. The time stamp represents the vehicle's local time at which the data point was generated. The sonar imaging data is represented as 2D grayscale images. In these images, 255 (white) represents a strong acoustic return while 0 (black) represents no acoustic return.

We provide two data sets from our experiments. The first is from the offshore deployment that images a mooring sinker block ('sinker_block_data.mat'), and the second is from the indoor pool test ('pool_data.mat'). Additionally, we provide our data processing files. These files consist of MATLAB scripts to view, annotate, and project feature points into the sonar images. A C++ template file is provided to aid the user in reconstructing 3D data points from their own annotated data. Additional details can be found in the README file. If the user further wishes to work with their own recorded data, we direct them to our ECD to CSV processing code, available at:
`https://github.com/osurdml/GeminiECD_Decoder`.

3 Results

3.1 Summary of Results

In section 3.2, the results show that using acoustic structure from motion (ASFM) algorithms allows for objects to be reconstructed in 3D using object feature points identified in sonar images. Section 3.3 illustrates that while a large percentage of sonar images can be of low quality (and lead to poor 3D reconstructions), it is possible to automatically distinguish between low and high quality images by characterizing them in terms of their 2D Discrete Cosine Transform (DCT) coefficients. In only using the predicted high quality images, precise 3D reconstructions can be maintained.

The goal for this milestone was to achieve mapping reconstruction errors less than 50 cm. An "X" target object with known dimensions of 0.35 x 0.35 x 0.44 meters (length, width, height) was reconstructed in a swimming pool, and a sinker block measuring 1 x 1 x 1 meters was reconstructed from an offshore deployment in sea states 3–4. The 3D reconstruction estimated the length and width of the "X" target object at 0.43 x 0.43 m (height was not estimated due to viewing the object from above) and the length and width sinker block as 0.9 x 1.1 m. These errors of approximately 0.1 m meet the requirements of the milestone.

3.2 3D Reconstruction

Figure 1 shows the output of the 3D reconstruction for the "X" object from one section of recorded data from a pool deployment. For this reconstruction, the "X" feature points in the sonar images are first reconstructed into 3D space. Next, using the known object proportions, a dense 3D point cloud is created. The ground truth size of the "X" object is 0.35 x 0.35 x 0.44 meters (length, width, height). Note that for this reconstruction, one edge of the "X" is not present. This is due to the fact that in this section of the recorded data, that edge is not visible in the sonar images (it is hidden in the sonar's acoustic shadow). The 3D reconstruction estimated the length and width of the "X" target object as 0.43 x 0.43 m compared to the ground truth of 0.35 x 0.35 m.

Figure 2 illustrates that even in the challenging case of the offshore deployment, a reasonable reconstruction of the sinker block's feature points is still able to be obtained. The length and width of the sinker block was estimated as 0.9 x 1.1 m (ground truth of 1 x 1 m), giving approximately a 10% error.

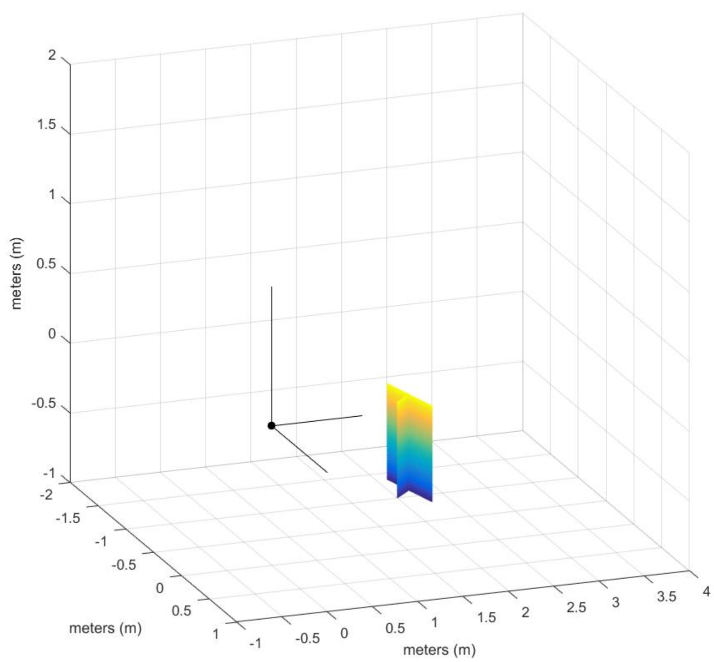

Figure 1: 3D point cloud reconstruction of a known object (3D "X") during a pool deployment. Feature points are first identified in 2D sonar images by an expert user before being reconstructed using recorded navigation data. The denser 3D point cloud shown is then generated from known object proportions.

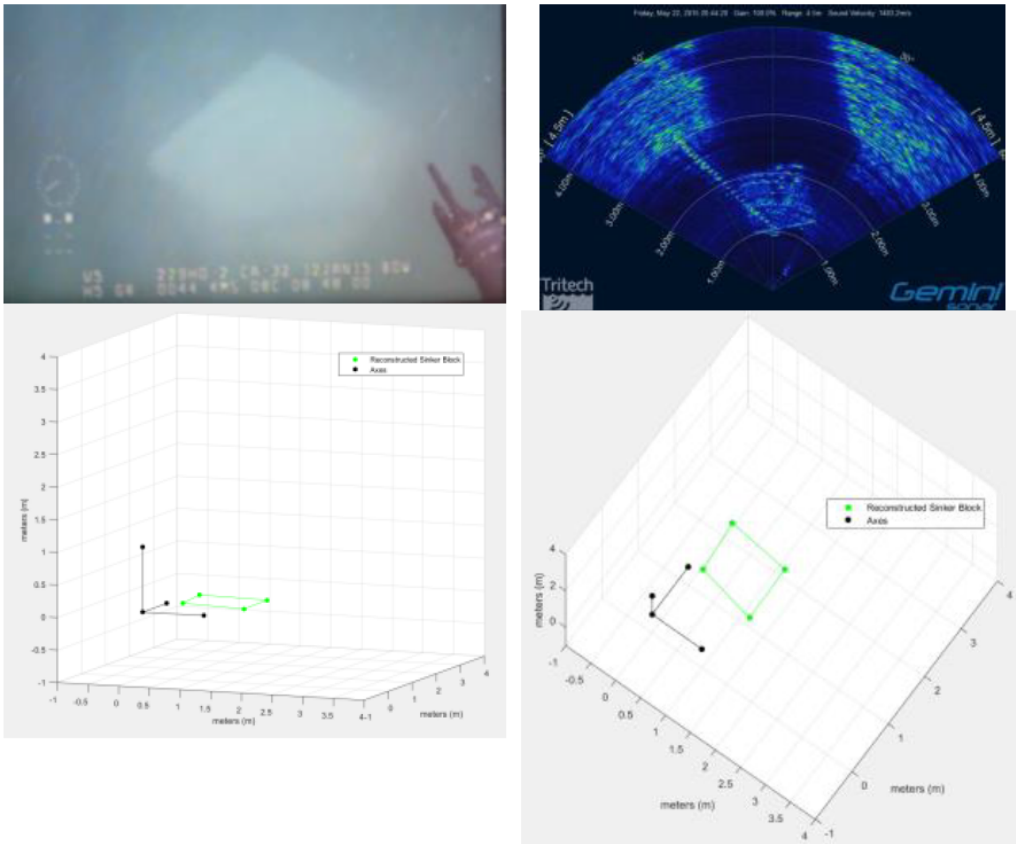

Figure 2: Top: Camera and sonar views of a mooring sinker block from the April 20, 2016 offshore deployment. Bottom: Two views (left) and (right) of a 3D point cloud reconstruction of a mooring sinker block. Feature points are first identified in 2D sonar images by an expert user before being reconstructed directly from the sonar images (no navigation data was needed).

3.3 Sonar Image Quality Analysis

When low quality sonar images are used to identify object feature points, inaccurate and variable labels occur. Using inaccurate feature point labels in the 3D reconstruction process results in arbitrarily poor reconstruction errors. In the experiments performed, this error was observed to be on the order of 100% - 400% of the reconstructed object's size.

Figure 3 shows that across several pool tests, it can be seen that the majority (more than 75%) of sonar images captured can be considered low quality. Figure 4 shows an example of both low and high quality sonar images and their corresponding DCTs. By utilizing only the sonar images identified as high quality, we are able to achieve the reported reconstruction errors of approximately 10%-20%.

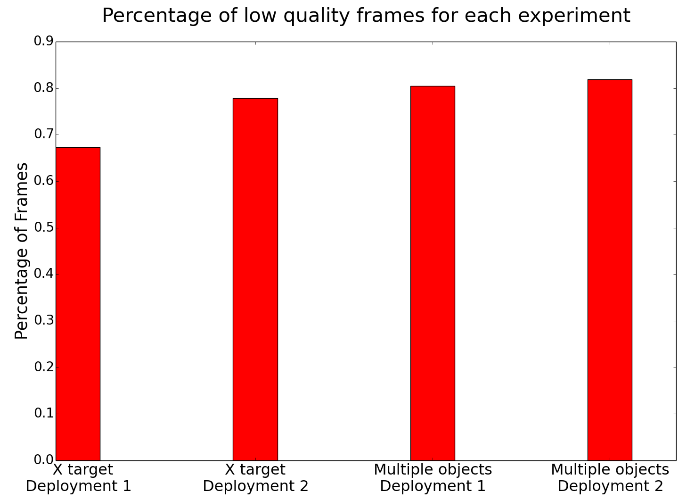

Figure 3: The percentage of frames that an expert user is unable to confidently hand label across multiple pool deployments. The first two data sets contain only an"X" shaped object, while the final two data sets contain the "X" shaped object among others (square, "T", and triangle shaped objects). On average, greater than 75% of the captured sonar images are not suitable for labeling.

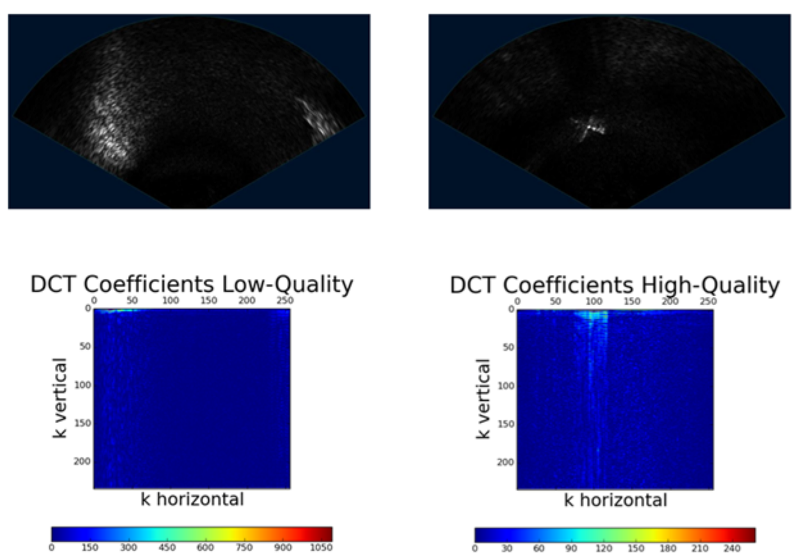

Figure 4: Low quality (left) and high quality (right) sonar images of the "X" object and their DCT coefficients. Coefficients closer to the bottom right corner indicate higher frequency information present in the image.