Underwater Depth Calibration Using a Commercial Depth Camera

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ABSTRACT

Depth cameras are increasingly used in research and industry in underwater settings. However, cameras that have been calibrated in air are notably inaccurate in depth measurements when placed underwater, and little research has been done to explore pre-existing depth calibration methodologies and their effectiveness in underwater environments. We used four methods of calibration on a low-cost, commercial depth camera both in and out of water. For each of these methods, we compared the predicted distance and length of objects from the camera with manually measured values to get an indication of depth and length accuracy. Our findings indicate that the standard methods of calibration in air are largely ineffective for underwater calibration and that custom calibration techniques are necessary to achieve higher accuracy.

CCS CONCEPTS

• **Hardware** → *Semi-formal verification.*

KEYWORDS

Underwater stereo vision, depth camera calibration

ACM Reference Format:
Emily M Wong, Isabella Humphrey, Scott Switzer, Christopher L Crutchfield, Nathan Hui, Curt Schurgers, and Ryan Kastner. 2022. Underwater Depth Calibration Using a Commercial Depth Camera. In *The 16th International Conference on Underwater Networks & Systems (WUWNet'22), November 14–16, 2022, Boston, MA, USA.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3567600.3568158

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WUWNet '22, –05, 2022, November 14-16, Boston, MA

ACM ISBN 978-1-4503-9952-4/22/11…$15.00
https://doi.org/10.1145/3567600.3568158

1 INTRODUCTION

Underwater stereo cameras enable accurate and reliable measurement of lengths, surfaces, and volumes and have wide-reaching implications for marine biology research and 3D scene reconstruction [11]. For example, our FishSense 3D camera aims to automatically measure fish length underwater with the purpose of accurately analyzing fish population trends [12]. The data quality directly depends on depth measurement accuracy, which requires calibration methods.

There are three main types of depth camera: the structured light camera, stereo depth camera, and time of flight camera [7]. Stereo depth cameras compare images from two sensors placed a known distance apart. The triangulation of rays to key focal points between these images tells the camera the distance to the object. Many stereo depth cameras, including the camera in our study, additionally project infrared light onto a scene in order to improve the accuracy of the data, but can use any light when measuring depth [7].

Image quality is characterized by the resolution and contrast of an image. Unfortunately, both resolution and contrast are impaired when putting a camera underwater because of the propagation characteristics of light in water [8]. Light scattering also creates a blurring effect underwater, and wavelength absorption can create a reduction of color in images [1]. Low image quality makes it more difficult for stereo depth cameras to compare the necessary differences in images and calculate depth. Furthermore, the difference in the refractive index of air and water can cause inaccuracies in the camera's perception of depth. Proper calibration is required to ensure that the camera performs adequately underwater.

For our experiments, we chose to work with the Intel RealSense Depth Camera D455. This camera is low-cost, commercially available, and a prevalent model for depth sensing. It boasts a depth error of less than 2% at 4 meters in air. Intel additionally provides several tools to assist in its cameras' calibration. Since Intel RealSense cameras are a standard model and have been used in other studies [3], we believe that they well represent the commercial stereo depth camera selection. We will explore four methods of calibration for the Intel RealSense Depth Camera D455 and evaluate the accuracy and practicality of each method for both depth and length measurement. Our methods of testing and analyzing results may be extended to other calibration techniques as well.

Our findings indicate that calibrating a camera in air or returning it to its factory settings resulted in inadequate depth and length estimates when that camera was placed underwater. This finding further motivates our study.

While we were unable to successfully calibrate underwater using a pre-existing calibration tool, our results signify that aspects of the underwater depth and length estimates can be improved using these tools.

2 RELATED WORKS

Compared to in-air calibration, underwater calibration is subject to additional factors such as differences in light refraction of water. A study from 2015 examined underwater calibration techniques for general cameras, and asserts that "calibration must implicitly or explicitly model and compensate for the refractive effects of waterproof housings and the water medium" [10]. Although our focus is calibration of depth rather than calibration of the overall camera, because depth relies on detecting variations in images, refractive effects from the enclosure and water medium will similarly affect our system. This idea is enforced by a 1998 study which examined the orientation and stability of an underwater stereo video system as well as experiments around the testing of camera calibration [5].

Previous studies have largely focused on depth data as a means for reconstructing 3D scenes. Such approaches have included using a standard camera in combination with light projections [9] to compute the geometry of an underwater scene. Digumarti et al. calibrated a low-cost commercial depth camera using a mathematical model that accounted for refraction from the transparent housing and water, as a means to extract a 3D mesh [3]. While their paper does not specify which Intel RealSense depth camera was used, it does present an alternative method of underwater refraction correction through models.

Underwater depth cameras have wide-reaching implications for marine biology research. Because of advances in digital video image quality and stereo imaging systems, stereo cameras and paired single cameras are allowing for new possibilities in accurate and reliable measurement of 3-dimensional lengths, surfaces, and volumes [11]. These advances assist in the management of marine ecosystems and biomass estimates for purposes of conservation and aquaculture. For instance, a 2003 study used stereo-video measurements to capture the length and maximum body depth of free-swimming southern bluefin tuna, to remove the need for capture in fisheries and matriculture situations [4]. Another study used dual underwater cameras to remotely estimate fish size in order to characterize population dynamics, support visual census techniques, and collect data [2].

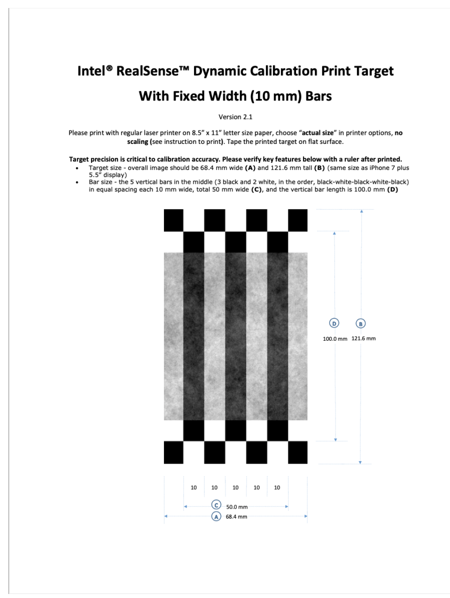
3 METHODS

Experiments were conducted both in and out of the water to establish a basis for comparison. We tested four methods of extrinsic calibration to improve depth and length estimates, namely, targeted calibration, targetless calibration, scale calibration, and hybrid calibration. We compared each of these methods with the baseline, or factory settings for the camera.

We tested each of these methods of calibration for three different states: the camera by itself, the camera in its enclosure in air, and the camera in its enclosure underwater. The enclosure places an acrylic lens over the camera with a thickness of 0.5 inches. Underwater tests were performed in a freshwater tank, which had a depth of around 0.6 meters. Two underwater video lights of around 8000 lumens each additionally helped in detection of the target underwater.

3.1 Targeted Calibration

The targeted calibration is recommended by Intel and the only mode supported by the Dynamic Calibration Tool API. A full depth length calibration takes the left and right camera images of a predefined target, followed by checks for rectification error [6]. Because the calibration target has specific, known dimensions, the camera is able to compare the measured pattern size with ground truth to improve the length estimation [6]. The calibration target can be seen in Fig 1, and was printed using Intel guidelines[1] on waterproof paper and then taped to a white board as shown in Fig. 2.


Intel® RealSense™ Dynamic Calibration Print Target

With Fixed Width (10 mm) Bars

Version 2.1

Please print with regular laser printer on 8.5" x 11" letter size paper, choose "**actual size**" in printer options, **no scaling (**see instruction to print**)**. Tape the printed target on flat surface.

Target precision is critical to calibration accuracy. Please verify key features below with a ruler after printed.

- Target size - overall image should be 68.4 mm wide **(A)** and 121.6 mm tall **(B)** (same size as iPhone 7 plus 5.5" display)
- Bar size - the 5 vertical bars in the middle (3 black and 2 white, in the order, black-white-black-white-black) in equal spacing each 10 mm wide, total 50 mm wide **(C)**, and the vertical bar length is 100.0 mm **(D)**

Figure 1: Intel RealSense Dynamic Calibration target, used for targeted calibration

The dynamic targeted calibration involves depth calibration and scale calibration. The depth calibration detects the target and determines distance away from the relative size. This step is difficult to complete underwater (see Section 5). The scale calibration, as will be described in the Scale Calibration section, uses the predetermined target size to scale length estimates [6].

[1]https://dev.intelrealsense.com/docs/dynamic-calibration-print-target

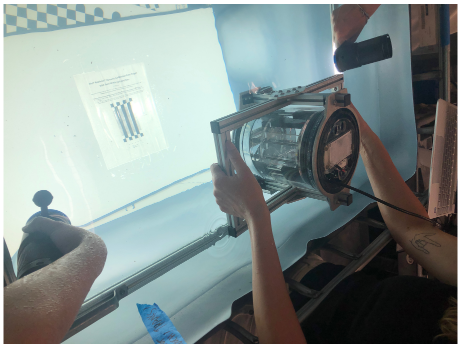


Figure 2: Camera performing underwater targeted calibration over an open tank of freshwater

3.2 Targetless Calibration

The targetless calibration method uses rectification by extracting features from left and right camera images and matching corresponding points from those features. Because the spacing between the left and right cameras is known, the depth can be calculated from differences in spacing of distinct points in the images. However, Intel notes that it is "generally less accurate and less consistent than targeted calibration" [6]. We used the borderless setting because of excess blank space in our testing tank. We experimented with different underwater settings and found that a board with multiple distinct points was most effective in completing the calibration. One such board is shown in Fig. 3. While the board that we used does somewhat resemble a target, it does not perform the same type of scaling as targeted calibration because it does not have previously determined lengths. Furthermore, any setting with distinct points would suffice for the targetless calibration, while only the Intel target works as a part of the targeted calibration.

Figure 3: Camera performing underwater targetless calibration over an open tank of freshwater

3.3 Scale Calibration

Scale calibration uses the same calibration target as the targeted calibration, but only uses the defined target size as a means to calibrate its length estimates [6]. It does little to calibrate distance from the camera to the target, and as such, Intel recommends it as a debugging tool. We used six images and increased the timeout time setting in order to fully complete the scale calibration.

3.4 Hybrid Calibration

Hybrid calibration combines the rectification method of the targetless calibration with the target detection of the scale calibration [6]. As such, it is meant to provide accuracy while minimizing use of the target.

4 RESULTS

We calculated the accuracy of the camera alone, the camera in the enclosure, and the camera in the enclosure underwater based on the average percent error for depth and the length. The depth percent error uses the difference between the camera's predicted distance to an object and the actual distance. Similarly, the length percent error uses the difference between the camera's predicted length using pixel depth data and the actual measured length of various objects.

In air, the tests of the camera alone and in the enclosure were performed by setting the camera on a steady base a specified distance away from two boxes of known length, width, and height. We then took the depth measurement of three separate spots in the same plane (i.e. three spots on the ground, three spots on the first box, and three spots on the second box) and compared the average of those depths with the known distance. To get the length component, we used the length feature from the Intel RealSense Viewer[2] to take measurements of the length and width of the boxes. The points for length measurements were visually selected using the RGB image while using the depth data at those points as reference. We also performed these measurements three times, to account for slight variations in user choice of start and end points. We then compared these lengths with the known lengths of the boxes, found using a measuring stick.

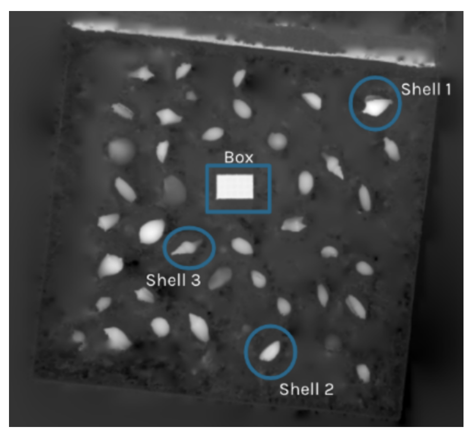


Figure 4: Underwater testing board with box and shells of known dimensions.

In water, experiments were conducted using a board with shells of known length and height. This ground truth data was generated

[2]https://www.intelrealsense.com/sdk-2/

Table 1: Average percent error of depth, for in air without the case, in air with the case, and underwater with the case.

Method	Air w/o Case	Air w/ Case	Underwater
Baseline	0.67%	2.72%	25.91%
Target	0.80%	1.53%	Unsuccessful Cal.
Targetless	0.08%	3.09%	2.31%
Scale	-	-	27.64%
Hybrid	1.35%	2.92%	27.51%

Table 2: Average percent error of length, for in air without the case, in air with the case, and underwater with the case.

Method	Air w/o Case	Air w/ Case	Underwater
Baseline	5.56%	4.38%	7.54%
Target	6.87%	5.23%	Unsuccessful Cal.
Targetless	5.08%	4.34%	25.87%
Scale	-	-	0.96%
Hybrid	6.37%	4.04%	8.41%

from a motion capture of the board, as shown in Fig. 4. The center of the board additionally had a box of known length, width, and height. For the underwater experiments we chose three shells with distinct shapes and conducted similar steps as the air tests; we took three depth measurements and three length measurements for each shell and for the box and compared them to the ground truth.

Our tests in air with the targeted, targetless, and hybrid calibrations yielded results very close to the baseline, or factory settings, both with and without the enclosure. Despite Intel's assertion that the targeted calibration was much more accurate than the targetless, the difference in air calibration results was not substantial enough to draw a definitive conclusion; both methods performed very similarly to the baseline factory settings. The average percent error of the depth, found by analyzing the distance between the camera and various objects of known height, was 0.80% for the targeted calibration and 0.08% for the targetless calibration. These results can be compared to the 0.67% average percent error in depth for the factory settings.

Adding the enclosure seemed to increase the average percent error in depth for all three of these calibration methods, while staying within what could be deemed an acceptable range. The average percent error of the targeted calibration rose to 1.53% and the error of the targetless calibration rose to 3.09%. The baseline camera increased to 2.72%. The percent error for the length of the image conversely decreased with the addition of the enclosure. The baseline percent error decreased from 5.56% to 4.38%, the target calibration percentage decreased from 6.87% to 5.23%, and the targetless calibration percent error decreased from 5.08% to 4.34% when the enclosure was added. All cameras notably had difficulty with finding the lengths less than 75 mm.

From the results in Table 1 and in Table 2, we can confirm that air-calibrated cameras have poor performance underwater for both depth and length estimations. The cameras calibrated in air with

Table 3: Average time of completion in minutes of five calibration methods, for in air without the case, in air with the case, and underwater with the case.

Method	Air w/o Case	Air w/ Case	Underwater
Baseline	N/A	N/A	N/A
Target	4.0	5.0	Timed out (>240)
Targetless	0.1	1.5	25
Scale	-	-	80
Hybrid	1.5	1	240

factory settings had an average percent error of 25.91% for depth and 7.54% for length when placed underwater.

Underwater calibration using the target proved to be unsuccessful after numerous failed attempts. The left and right cameras had difficulty in detecting the target while underwater.

Targetless calibration was the fastest method underwater, with an average calibration time of 25 minutes. Average calibration times in minutes can be seen in Table 3. While targetless calibration vastly improved the percent error for depth to an average of 2.31%, it did so at the cost of length accuracy. The average percent error of the length increased to 25.87% with relatively uniform error for every length test.

We hypothesized that hybrid calibration, which combined the depth portion of targetless calibration with the scaled target portion of scale calibration, would yield the best results. Conversely, hybrid calibration performance was subpar in both categories with a percent error of 27.51% for depth and 8.41% for length, as can be seen in Table 1 and Table 2. As can be seen in Table 3, it additionally took the longest time to complete underwater with a calibration time of 4 hours.

5 DISCUSSION

From our findings we can deduce that, in air, our tested calibration methods produced fairly precise depth and length accuracies. These can be deemed effective because of their similarities to each other and to the Intel RealSense camera factory settings, or baseline. However, our findings also indicate that depth cameras calibrated in air are inaccurate when placed in water. Furthermore, accuracies for both depth and length estimates vary widely for cameras calibrated and tested underwater. This lack of trends and appearance of randomness in the underwater data imply that these calibration methods, which are effective in air, are relatively ineffective in water. This finding reinforces our need for a proper underwater calibration technique.

Calibration involving a target proved to be difficult to complete, often taking several hours of attempted detection if the process was able to finish at all. We predict that this prolonged calibration time is due to the inability of the camera to detect the contours of the specific target while underwater. As discussed in the Introduction, images in water often have lower resolution and contrast, which can make it difficult for cameras to detect the specific points necessary for many of our calibration methods. We hypothesize that the targetless calibration was more effective because it could use any distinct points, not just the Intel target.

In conclusion, pre-existing depth calibration tools can be powerful and effective resources for stereo depth camera calibration in air, but yield percent errors over 25% when attempted underwater. Future studies may examine custom calibration techniques for situations that require more accurate depth and length estimates underwater. We are also pursuing OEM Calibration techniques, which should be better able to impact the camera's intrinsic parameters like focal length, principal point, and distortion [6]. This method was not examined previously because of the difficulties in exact placement of the camera and OEM Calibration Target while underwater.

ACKNOWLEDGMENTS

This work was funded in part by the REU Site Engineers for Exploration, supported by the NSF under Grant No. 1852403 and the NVIDIA Applied Research Accelerator Program. We would also like to acknowledge our collaborators at the Semmens Lab at Scripps Institution of Oceanography for making this research possible.

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