Modifiable Distance Object Following and Obstacle Avoidance in Autonomous Underwater Robotics

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Introduction

Autonomous robotics is a rising sector in the field of robotics, with applications ranging from Roombas, residential vacuum cleaner robots [1], to Astrobee, an autonomous low-gravity robot aboard the International Space Station [2]. One promising application of autonomous robotics is underwater robotics, in which robots assist divers in multiple tasks, including exploration, data collection, and mapping. A significant area of interest is that of entirely unmanned missions, wherein a robot will complete these tasks without the guidance of a diver or teleoperation, the remote operation of a robot by a human operator. Without humans involved, such a robot can operate with less human effort, resulting in lower costs and fewer errors. Algorithms that enable underwater robots to track and follow a subject of interest while avoiding obstacles can be very valuable.

One use case of such algorithms is studying the behavior of marine life in the field. To gather the necessary footage, a robot will need to observe the targeted marine life from a distance and follow it without disturbing it, or risk compromising the behavior of the subject, a task humans may unintentionally fail at, or be unable to complete. One additional case is that of search and rescue. If in open water, a stranded person is discovered by such a robot, it could follow the person in question and periodically alert rescue personnel to their location, or determine their distance to deploy a floatation device. While following a subject, the robot will likely encounter obstacles, including marine debris and marine life, which could damage the robot. As such, a necessary facet of the algorithms is identifying objects in the field of view, distinguishing a target subject from obstacles, and identifying a path around obstacles.

Past Work

This research would implement a tracking and following algorithm that a robot, with enough training data, could track and follow a subject of interest, including marine life, as well as maintaining a desired distance from the subject. Islam et al [3] has developed an algorithm for an autonomous underwater robot to track and follow a diver, both in controlled environments and in the field. The proposed work would build upon this algorithm to track and follow divers by generalizing the object being followed to marine life or marine debris and adding the functionality to maintain a specified distance. Mobile robots will typically encounter obstacles in their path, making obstacle avoidance a key challenge, but in several applications, this problem has been solved. For example, Borenstein and Koren have developed a method for land-based robots to avoid obstacles using a vector field histogram [5]. *The key challenge in this application is that both the robot and the obstacles have 6 degrees of freedom when underwater, whereas in past work, the robot and the obstacles could only have 3 degrees of freedom.*

Methodology

We will use the diver tracking algorithm put forward by Islam et al [3] to track and follow divers, and train it to follow marine life or other subjects of interest, as well as create a module to allow others to train it with their own dataset. As shown by Smolianskiy et al, despite improvements in monocular learning algorithms, stereo cameras are still essential for estimating depth when compared to deep-learning algorithms and a single camera [4]. As such, stereo cameras will be used for depth estimation using the intuitive method specified in the OpenCV documentation [8]. OpenCV is a popular open-source computer vision library in multiple programming languages with multiple helpful functionalities and will be used heavily in this proposed research. *The key challenge will be applying the generalized diver tracking algorithm with multiple cameras and reconstructing depth*.

Obstacles in the field of view will be segmented from video provided by stereo cameras. For our applications, detection or recognition of objects in the field of view will not suffice due to the large amount of empty space that exists in bounding boxes typically constructed during detection and recognition. A form of image segmentation, the identification of the individual pixels that constitute an object in an image, is necessary for a robot to effectively navigate an environment that may contain several obstacles wherein a bounding box containing the obstacle is relatively sparse. Specifically, Wang et al surveys and discusses several influential methods of video segmentation [9]. These methods will be assessed and implemented. Annotated datasets, such as the TrashCan 1.0 dataset, a dataset of underwater trash and marine life by Hong et al [6], can be used to apply, train, and debug the methods of segmentation by Wang et al.

Impact

This project is intended to integrate multiple necessary facets of autonomous underwater robotics. If successful, this research project would bring underwater robotics closer to being fully autonomous by enabling underwater robots to operate without the direction of a diver, resulting in less human effort, lower costs, fewer errors, and the completion of missions that humans cannot complete. The proposed work would facilitate ecological data collection, unmanned search and rescue, and several other applications requiring unmanned underwater exploration.

This research will be conducted under the supervision of Professor Junaed Sattar in the Interactive Vision and Robotics Laboratory (IRVLab) at the University of Minnesota. Professor Sattar has significant experience in underwater robotics, having developed both the diver following algorithm and the TrashCan dataset. This research project aligns with his and the IRVlab's goals of furthering research in autonomous underwater robotics and human-robot interaction.

References

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