Out of Distribution Detection for Safe Underwater Infrastructures using Computer Vision

Azad Md Abulkalam

Erasmus Mundus MIR, Université de Toulon, France

MARINE & MARITIME INTELLIGENT ROBOTICS

Co-funded by the Erasmus+ Programme of the European Union

Introduction

- Underwater infrastructures such as oil, gas or aquaculture industries are growing everyday
- The demand for regular underwater operations such as inspection, maintenance and repair (IMR) is also increasing
- Manual IMR operations are expensive, life-threatening, and prone to wrong operations and thus accident
- Vision-based adaptive autonomy can increase safety and reduce cost
- But this autonomy may fail when it encounters an unprecedented situation (Out of distribution)
- Because prediction of deep learning model on OOD data is sometimes wrong with high confidence
- Therefore, enabling OOD detection to vision-based autonomy can mitigate the issue and ensure the safe underwater infrastructure

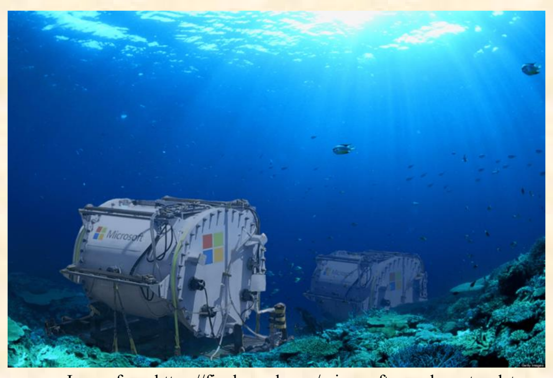


Image from https://finchannel.com/microsoft-s-underwater-data-center-rises-from-the-sea-after-two-years/

Image from http://isciencemag.co.uk/features/relying-on-underwater-cables-spells-disaster-for-the-internet/

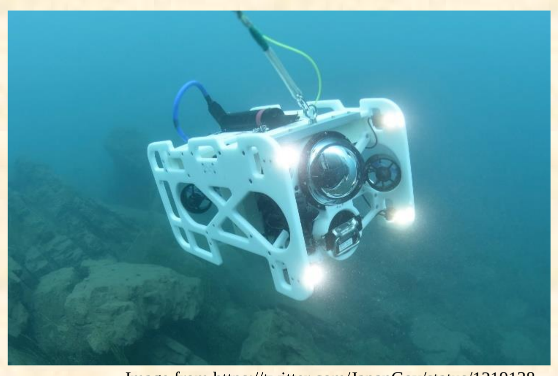


Image from https://twitter.com/JapanGov/status/1219138883440410624-/photo/2

Motivation

- Computer vision has great potential in underwater robotics
- Remotely Operated Vehicles (ROVs) or Autonomous Underwater Vehicles (AUVs) are used extensively in the underwater industry
- The integrated camera can be utilized to adopt vision-based technology in their regular operations along with OOD detection
- Fish escaping in aquaculture due to mooring failure, breakdown of net cage structure, abrasion, and tearing of nets is a big concern [1]
- Regular inspection using vision to detect irregularity or damage can avoid this issue
- Identification of individual fish in the net cage for inspecting the health and well-being
- Vision-based OOD detection can discover new underwater species [2]
- Underwater intervention can also be benefitted by detecting cracks in oil/gas pipes
- In defense mechanism, trespassing of an intruder can be detected
- Illegitimate activities of an intruder can be observed

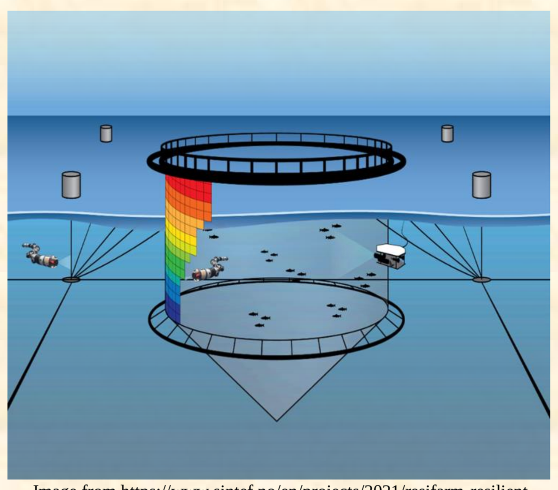


Image from https://www.sintef.no/en/projects/2021/resifarm-resilient-robotic-autonomy-for-underwater-operations-in-fish-farms/

Image from https://www.republicworld.com/technology-news/science/atlantic-researchers-discover-12-new-marine-species-hiding-in-the-deep-sea.html

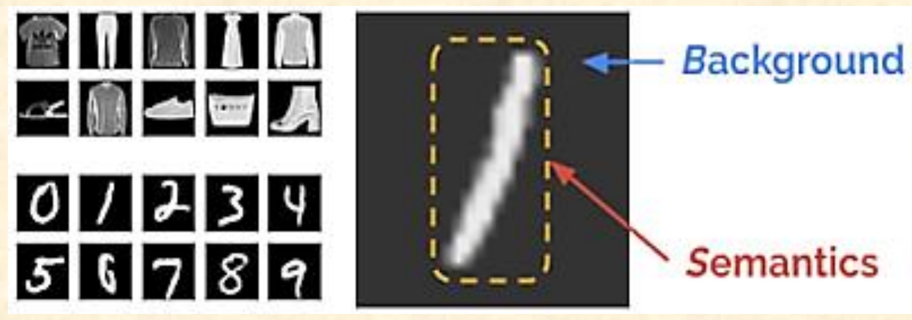
Background

- A substantial research is focusing on to reach the full safe autonomy using vision
- In [3], vision-based motion estimation and obstacle detection are integrated into autonomous underwater mission planning system
- Visual simultaneous localization and mapping (VSLAM) is introduced into the system
- It increases the autonomy by situation awareness, accurate local positioning, and obstacle detection
- In [4], an autonomous grasping of underwater objects by a robot manipulator arm named SeaArm-2 has been proposed
- This manipulator is integrated with a monocular camera near to the gripper
- This vision-based grasping system can alone percept, detect, and localize the object without any external sensors
- In [5], a Dynamic Positioning (DP) system for underwater vehicle relative to an object has been proposed

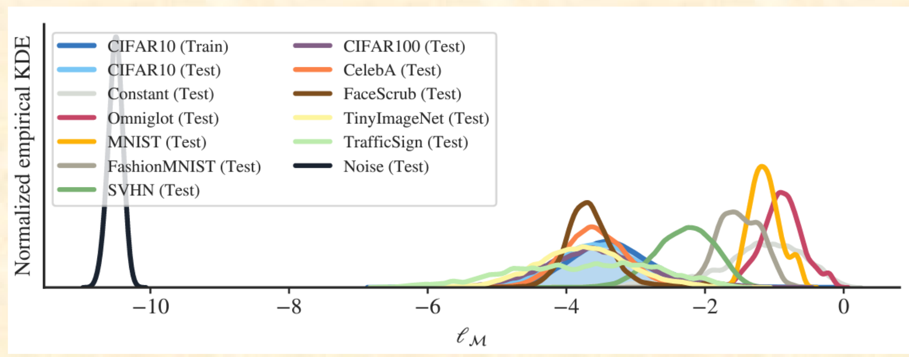
- The object of interest is detected on the run using vision based on the YOLOv3 object detection framework
- After computing the distance, the motion control system keeps the ROV at a fixed position and heading angle

State-of-the-art

- There are different improved approaches to vision-based OOD detection
- In [2], the authors assume there are two components in an input data,1) background and 2) semantic (e.g. an image consists of background and object)
- They only want the likelihood of semantic part and avoid the background part for OOD detection



- Therefore, they take the ratio of the likelihood of these two components
- This cancels out the likelihood for the background part and keeps only the semantic likelihood
- In [6], it shows that likelihoods computed from generative models exhibit a strong bias towards the complexity of the corresponding inputs
- It found that qualitatively complex images tend to produce the lowest likelihoods, and that simple images always yield the highest ones

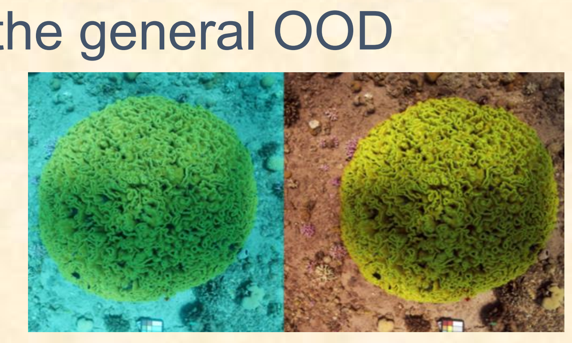


- Consequently, it proposes to leverage such estimates of complexity to detect OOD inputs
- One more recent study [7] shows that current state-of-the-art generative model OOD scores are much less effective for Variational Autoencoder (VAE)
- Therefore, proposes a new OOD score called Likelihood Regret which shows a promising result in their evaluation

Expected thesis contribution

Since most of the state-of-the-art OOD detection methods are based on general vision problems,

1. An important contribution will be to implement those methods for underwater environment
2. Finding the best method by qualitative and quantitative comparisons among those methods
3. Propose improvements to OOD detection by taking into consideration the nature, difficulty, and complexity of underwater environment
4. One evolution can be, to remove water from the underwater images using Sea-thru [8] and then use the general OOD detection methods



Therefore, the successful completion of the contributions can bring the safety or explore the unknows in underwater infrastructures.

References

1. H. Ø. Karlsen, H. B. Amundsen, W. Caharija, and M. Ludvigsen, "Autonomous aquaculture: Implementation of an autonomous mission control system for unmanned underwater vehicle operations," in OCEANS 2021: San Diego–Porto. IEEE, 2021, pp. 1–10.
2. J. Ren, P. J. Liu, E. Fertig, J. Snoek, R. Poplin, M. Depristo, J. Dillon, and B. Lakshminarayanan, "Likelihood ratios for out-of-distribution detection," Advances in Neural Information Processing Systems, vol. 32, 2019.
3. F. Gao, S. B. Moltu, E. R. Vollan, S. Shen, and M. Ludvigsen, "Increased autonomy and situation awareness for rov operations," in Global Oceans 2020: Singapore–US Gulf Coast. IEEE, 2020, pp. 1–8.
4. M. B. Skaldebø, B. O. Haugaløkken, and I. Schjølberg, "Seaarm-2-fully electric underwater manipulator with integrated end-effector camera," in 2021 European Control Conference (ECC). IEEE, 2021, pp. 236–242.
5. M. Skaldebø, B. O. A. Haugaløkken, and I. Schjølberg, "Dynamic positioning of an underwater vehicle using monocular vision-based object detection with machine learning," in OCEANS 2019 MTS/IEEE SEATTLE. IEEE, 2019, pp. 1–9.
6. J. Serr`a, D.´Alvarez, V. G´omez, O. Slizovskaia, J. F. N´u˜nez, and J. Luque, "Input complexity and out-of-distribution detection with likelihood-based generative models," arXiv preprint arXiv:1909.11480, 2019.
7. Z. Xiao, Q. Yan, and Y. Amit, "Likelihood regret: An out-of-distribution detection score for variational auto-encoder," Advances in neural information processing systems, vol. 33, pp. 20 685–20 696, 2020.
8. D. Akkaynak and T. Treibitz, "Sea-thru: A method for removing water from underwater images," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 1682–1691.

UNIVERSITÉ DE TOULON
NTNU Norwegian University of Science and Technology
UNIVERSITAT JAUME I
TÉCNICO LISBOA