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ADVANTAGES AND LIMITATIONS OF USING CAMERAS ON SMALL, LOW-COST ROVS FOR SEABED MONITORING

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Eyeball-class ROVs for Monitoring

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Researchers from Denmark investigate the potential of a non-invasive and simple underwater remotely operated vehicle to enhance seabed monitoring.

Who should read this paper?

This paper is of interest to marine researchers involved in monitoring the marine environment. Readers are introduced to the advantages and limitations of using cameras on small, low-cost ROVs, which can help with decision-making on monitoring equipment. Policy-makers and marine managers can also benefit from understanding the practicality of using these ROVs for ecological monitoring in areas with limited resources. Additionally, this paper addresses the shortcomings of ROVs and camera solutions, which can be helpful for the camera industry and underwater image enhancement research.

Why is it important?

The paper focuses on evaluating the performance of a small, low-cost ROV for monitoring marine environments. The study demonstrates how these eyeball-class ROVs can provide valuable data across various substrates, including challenging conditions like strong currents and turbid, murky waters. It emphasizes the flexibility of ROVs compared to traditional tools like towed cameras or sampling equipment. Additionally, it highlights the potential to revolutionize species identification through post-processing tools and eDNA integration, sparking excitement about the advancements in low-cost monitoring and marine research.

As the first study to use cameras in this part of the Greater North Sea, sparse taxa communities were observed in stone reefs and sandy substrate. These findings provide a deeper understanding of marine habitats, which can guide future research and contribute to better ecological management, biodiversity conservation, and the development of informed protection measures for critical marine habitats.
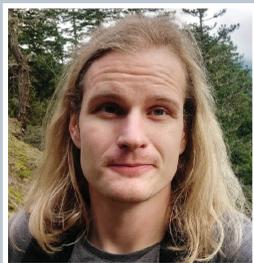
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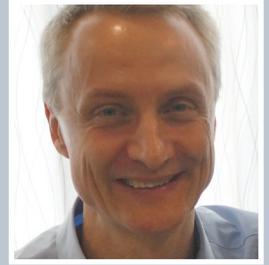
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ABSTRACT

Monitoring methods, such as seabed bottom-towed cameras, sediment grabs, and benthic sledges, have limitations in spatial coverage, cause seabed disturbance, are restricted to soft-bottom substrates, and offer low flexibility for marine seabed monitoring. In this study, we investigate the potential of a non-invasive and simple underwater remotely operated vehicle (ROV) to enhance marine seabed monitoring. A tethered ROV equipped with a GoPro camera was deployed in three areas of Skagerrak at depths from 15-34 m to assess accuracy in species identification and substrate classification identified from still frames. The quality of still frames varied between areas due to turbidity, motion blur, and marine snow, which reduced the number of high-quality frames by approximately 20%. Classification of substrates and taxa identification were possible in the remaining still frames. Two different substrates were detected: sand and stone reef. Stone reefs had a lower occurrence compared to sand. A total of 10 taxa were detected in the two substrate types. The highest abundance was observed in the stone reef substrate compared to the sand substrate. Identification at the species level was limited due to the quality of the still frames, which affected the detectability of morphological traits. This study demonstrates that a widely accessible ROV can be used for marine monitoring. The ROV can be used in different substrates, and still frames provide valuable information on species composition, which can enhance the replicability of monitoring programs.

Keywords: Drones, Greater North Sea; Image quality; Marine habitats; Remotely operated vehicle; Species identification; Underwater video camera

1. INTRODUCTION

Monitoring marine environments is essential as it provides valuable information that enhances scientific understanding of marine ecosystems and supports management and sustainable development. The marine environment is currently under pressure from climate change, pollution, and exploitation of marine resources [1] and comprehensive monitoring programs are important for marine protection. Within the European Union (EU), the Marine Strategy Framework Directive (MSFD) requires all member states to achieve Good Environmental Status for the marine environment [2], [3]. Since its implementation, EU nations have adopted monitoring programs that often overlap with other Marine Protected Area programs, such as the European Nature 2000 and EU Habitat Directive, which are implemented to protect rare, endangered, and characteristic species and habitats [4]. Member states are free to choose the sampling design and assessment methodology, which can limit the robustness and replicability of the monitoring program. In MSFD, methods such as seabed towed cameras, sediment cores, grabs, and sonars are deployed from vessels, or data is collected by observations from divers [5], [6], [7]. These methods either require a high expertise level, are spatially restricted in terms of coverage, have difficulties operating in hard substrates, lack flexibility in movement, or disturb flora, fauna, and substrate when towed on the seabed [8], [9], [10], [11], [12].

As an alternative monitoring tool, remotely operated vehicles (ROVs) – such as underwater drones and drop cameras – have been successfully used in marine monitoring, providing marine scientists with a powerful tool that enhances monitoring capabilities [13], [14], [15], [16], [17], [18]. These camera solutions are non-invasive with limited disturbances to the seabed, function on hard substrates, can be deployed in remote locations, provide long-term monitoring that ensure replicability, and provide information of an environment [14], [16]. However, these methods are not accessible to all monitoring parties due to their high cost, the need for larger vessels for deployment, and the logistical challenges. An emerging option is affordable open-source underwater ROVs that are small and lightweight, typically weighing only 2 kg. These ROVs have adjustable speeds ranging from about 3 knots to standstill, can dive down to 200 m (depth rating), and have tether lengths that allow ranges up to 400 m. The tether ensures a live video feed that can be used to inspect and avoid collision. Launching from the surface is easy with a simple tether system, and the ROVs are easy to control remotely, offering high manoeuvrability due to the fast-responsive thruster. As a standard, ROVs come equipped with 4K cameras, and most include floodlights, allowing for monitoring in dark and turbid waters. These ROVs have been used experimentally [19], in the aquaculture context [20], and for ecological purposes [21], all proving to be useful.

In this study, we tested if substrate type and species composition could be detected from frames provided by cameras mounted on a low-cost ROV system and how information hereof can be used in seabed monitoring. We focused on an area in the Greater North Sea in the southern Skagerrak with strong current and murky turbid waters. These conditions can

reduce the quality of frames and complicate extracting ecological information. Moreover, comprehensive monitoring programs to support effective management decisions are missing in this area, and we aim to identify the advantages and limitations of small, low-cost ROVs for seabed monitoring.

2. METHODS

2.1 Study Sites
The study was conducted in the Greater North Sea (Skagerrak region, ICES area 3a) (Figure 1). The study area features shallow coastal waters influenced by tides. The North Atlantic current runs from south to north, mixing the water and maintaining salinity between 33-35‰ and temperatures ranging from 6 to 17°C depending on the time of year. The depth in the study area gradually decreases from the coast to approximately 40 metres. This area is one of the most intensively fished areas globally, utilizing various bottom-towed fishing gears [22], and it also includes Marine Protected Areas such as Natura 2000 [4].

The sampling activities targeted three areas with varying depth profiles and distances from the coast. Area A was 12-16 nautical miles from the coast with depths between 31-34 metres, Area B was 5-7 nautical miles from the coast with depths between 15-23 metres, and Area C was 7-10 nautical miles from the coast with depths between 24-28 metres (Figure 1). The ROV was deployed at four sites within each of these areas.

2.2 Video Camera and ROV
The seabed examination was conducted using a tethered ROV, specifically the Chasing m2 Pro Max (Chasing, China) (Figure 2a). The ROV has a maximum speed of 3 knots and a battery life of approximately 1.5 hours, depending on the duration of recordings, use of lights, and thruster activity. It features a standard 4K resolution camera and is equipped with two 4000-lumen floodlights. This camera was used solely for navigation, as configuring its settings to our needs was challenging.

A GoPro Hero Black 11 camera (GoPro, USA) was mounted and tilted at a 45° angle from the ROV (Figure 2a), providing an oblique view of the seabed. The GoPro was used as the main camera and provided the frames used in substrate and fauna classification. The GoPro camera records GPS data at one-second intervals, enabling geolocation of collected data by interpolating the last position recorded before submerging the ROV with the first after resurfacing, thus allowing the ROV's path estimation. The lights were positioned to limit backscatter in the GoPro camera recordings.

The ROV was deployed at predetermined sites and positioned approximately 0.5-1.5 metres above the seabed, allowing it to drift with the survey vessel for approximately a 15-minute interval.

2.3 Analysis of Video Recordings
Only one frame per 10-second recording was retained to ensure comprehensive data without overlap in frames, thus covering most of the area. The first frame in each block was selected for annotation. Additionally, the analyst reviewed the frame directly before and after the selected frame to identify potentially hidden organisms. All frames were annotated using the open-source software LabelMe (https://github.com/wkentaro/labelme).
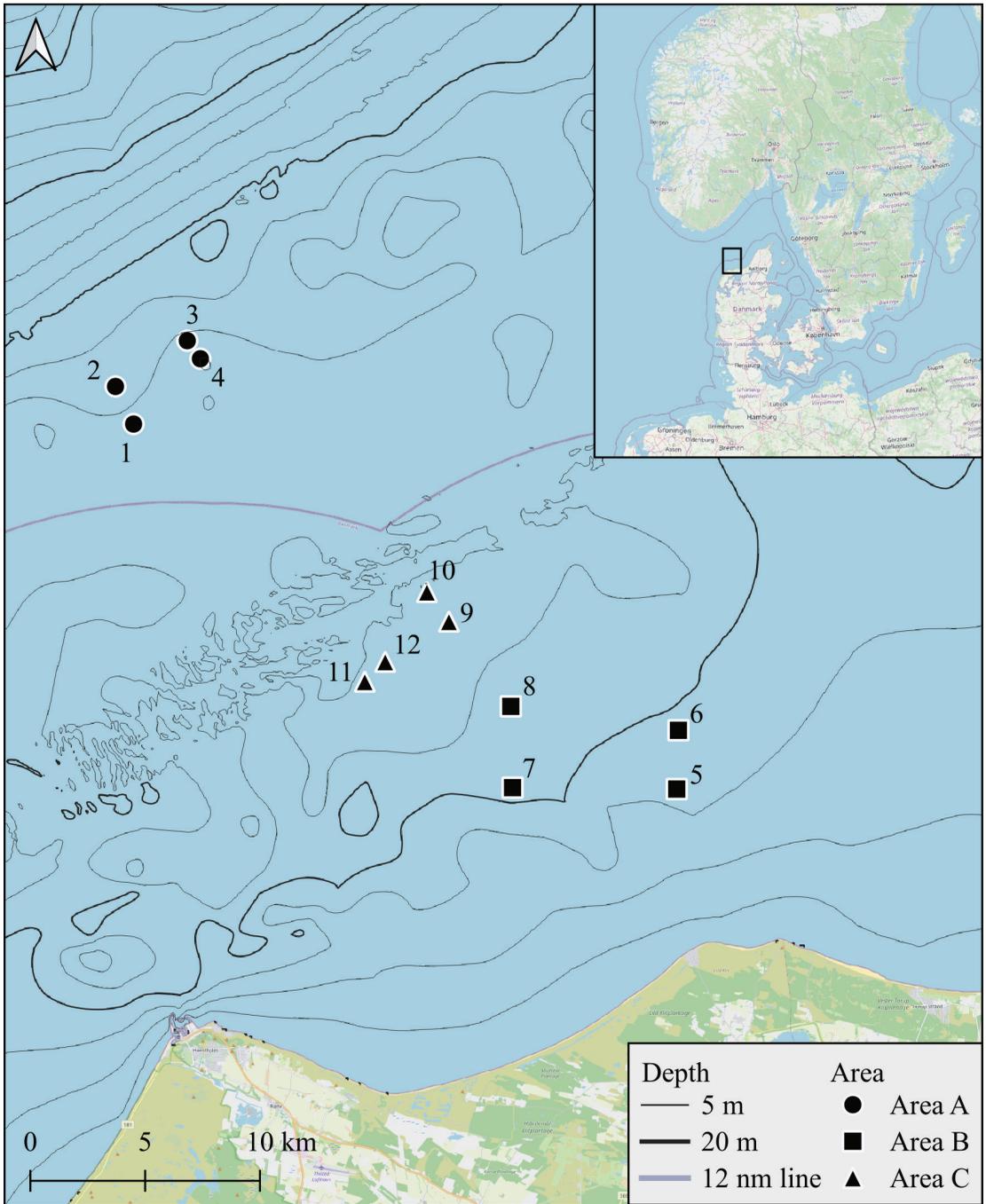
Figure 1: Sites for recording with underwater ROV in the Greater North Sea off the northwest coast of Denmark. The sampling sites are shaped per area: A) circle, B) square, and C) triangle. The number adjacent to the point shows the site number. The lilac line is the 12-nautical-mile line that indicates where the Danish territory ends. Made with QGIS.
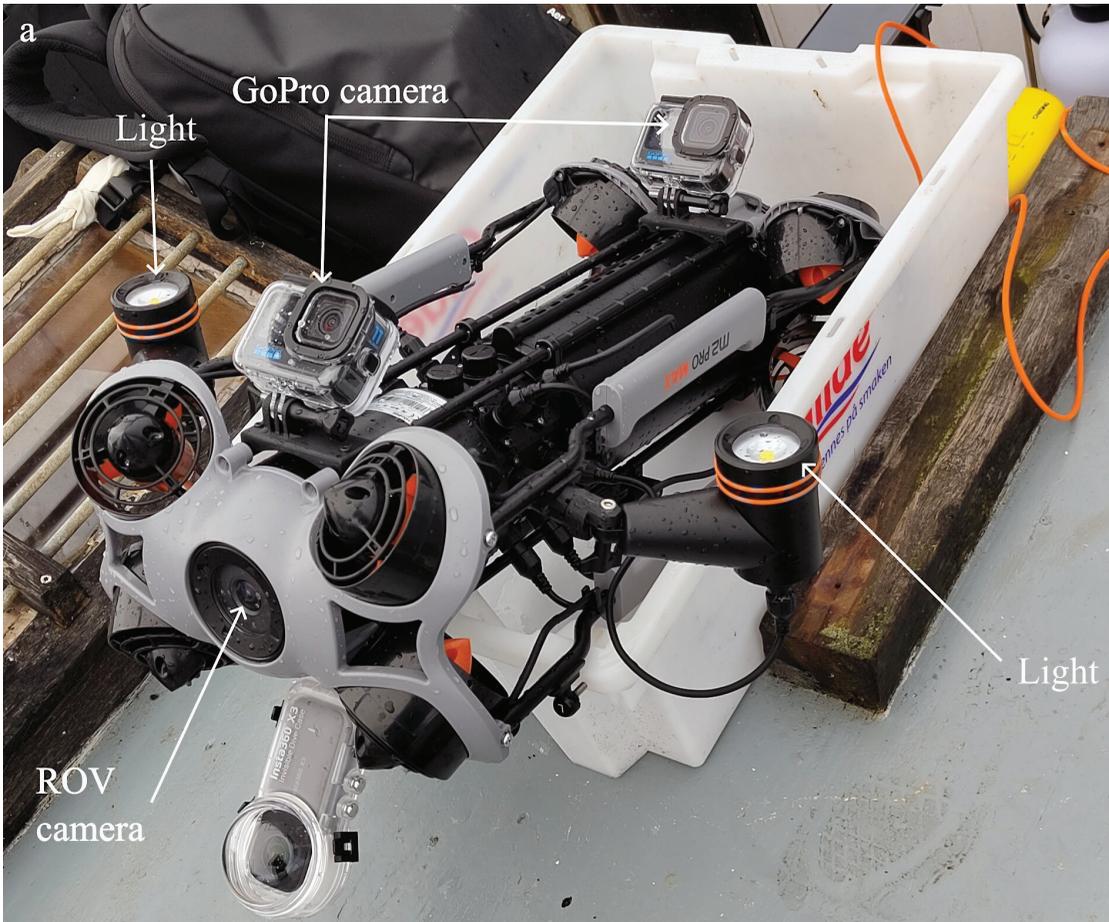
Figure 2: a) The ROV mounted with two cameras at the bottom (bottom of the photo) with lights on both sides.

In cases where the entire frame and video were blurry, had a high level of marine snow, or the camera angle was off the seabed, the whole block was labelled low quality. When the seabed was visible, taxa were noted and classified. Frames were labelled as low quality if taxa could not be detected.

Each frame was labelled according to its substrate, either stone reef or sand, as per the definition in section 2.4.

2.4 Substrate Classification

The substrates observed in the frames were classified based on the revised European Nature Information System (EUNIS) habitat classification [23]. EUNIS is a comprehensive classification system for European terrestrial and marine substrates based on descriptors and environmental parameters. The classification system is hierarchically structured and includes an online key [24]. Using this key, two substrate types are identified:

- Sand (*MC52 Atlantic circalittoral sand* [25]) are substrates predominantly made up of sand and, to some degree, affected by wave actions or tidal currents. These are found between 0-50 metres. Sand substrates must have a minimum of 70% cover in this study and have mussel shells and stone with less than 30% cover.
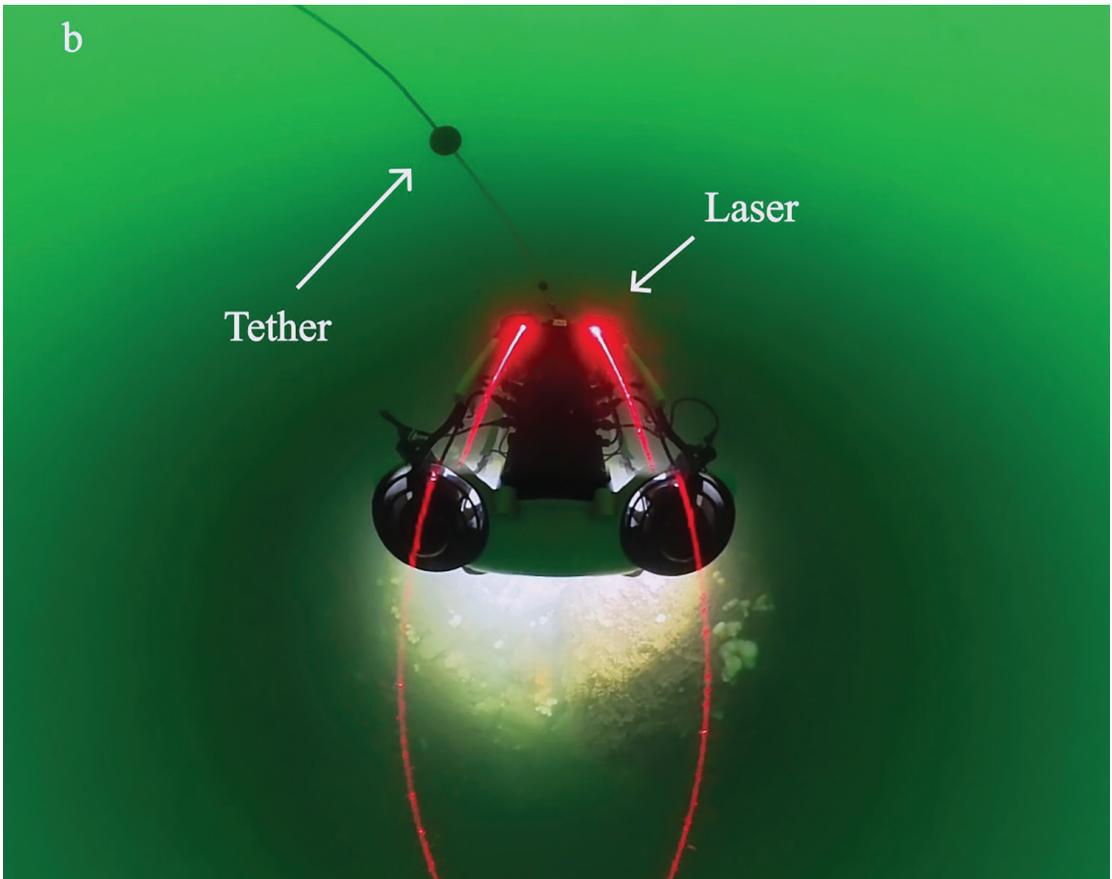
Figure 2: b) The ROV in the water with the red laser beams 10 cm apart, which allows for measuring objects (not used in this study).

- Stone reef (*MC12 Atlantic circalittoral rock* [26]) is classified as predominantly bedrock and boulders at 10-50 metres depth and subject to tidal stream. This study classified areas with more than 30% rock cover (determined by visual inspection) as stone reefs.

2.5 Taxa Identification

Every frame was annotated for all fauna taxa to the most specific taxonomic level possible. A cautious approach was taken in cases where there was uncertainty in classification due to low resolution, obscured views (e.g., behind objects or in the background), or morphological similarities that made it difficult to distinguish taxa based solely on the frames. In such instances, annotations of taxa were kept to lower-taxonomic resolutions (e.g., genus, family) to avoid incorrect classifications.

Quantitative measures of taxa included taxa richness and abundance to determine taxa composition. Taxa richness was defined as the total number of unique taxa and abundance as the total number of individuals. Both were determined by counting the total number of different taxa and individuals observed within each site. Taxa richness and abundance were determined in two groups: one included all individuals at the highest taxonomic level, and the second included only taxa identified at the species level. The second group was included

Table 1: Overview of sampling efforts with the ROV at each site with the corresponding date (DD-MM-YY), depth (in metres), and the data output in the number of frames extracted from the camera, recording time, number of frames annotated as high- or low-quality frames, and substrate (sand, stone reef, non-identifiable). All frames are publicly available at https://www.kaggle.com/amandairlind/datasets.

Area	Site	Date	Depth (m)	Sampling		Frames				
				Frames (No.)	Recording (Min.)	High quality	Low quality	Sand	Stone reef	Non-identified
A	1	08-11-2023	34	221	36.8	211	10	73	142	6
	2	08-11-2023	32	54	9.0	52	2	54	0	0
	3	08-11-2023	26	67	11.2	61	6	67	0	0
	4	08-11-2023	33	70	11.7	67	3	70	0	0
B	5	26-09-2023	15	97	16.2	10	87	39	0	58
	6	26-09-2023	19	58	9.7	44	14	47	0	11
	7	26-09-2023	21	163	27.2	154	9	53	107	3
	8	10-11-2023	24	95	15.8	78	17	20	61	14
C	9	07-11-2023	26	29	4.8	14	15	13	8	8
	10	07-11-2023	27	56	9.3	78	38	21	9	26
	11	07-11-2023	25	45	7.5	39	6	40	0	5
	12	07-11-2023	24	21	3.5	15	6	16	0	5
Total				976	163.0	763	213	513	327	136

to assess the extent at which taxa can be classified at the species level using frames.

2.6 Visualization

Visualizations were made in R version 4.3.1 via RStudio version 2023.06.2+561 (http://www.rstudio.com) using the packages dplyr [27], Tidyverse [28], and ggplot2 [29], and in QGIS version 3.32.1.

3. RESULTS

3.1 Evaluation of ROV Performance

Overall, the ROV was easy to handle when launching, manoeuvring, live video feed, and retrieving. The live video feed and the remote control allowed adjustments of the ROV's direction or distance from the seabed when obstacles, mainly large stones, appeared in its path. It was possible to maintain the ROV's stability while drifting at 1-2 knots with minimum thruster usage. Stronger currents (above 2 knots) resulted in shorter recording times and increased motion blur (unclear focus of objects). The thrusters were used to counteract the strong current, but this increased battery consumption. In strong current sites, particularly in Area C, half of the battery was depleted after 30 minutes, whereas approximately 25% of battery power remained in sites with less current (Area A). Significant battery consumption occurred during the ROV's deployment and retrieval to counteract drifting caused by waves and swells. Generally, we observed that battery power consumption correlated with current strength but not depth. In Area A (depth 26-36 m) (Table 1), the ROV had more battery power remaining after retrieval than in Area B (depth 15-24 m) and Area C (depth 24-27 m).

3.2 Sampling and Quality of Recordings

Sampling resulted in 976 frames covering 163 minutes of seabed recordings, with 763 high-quality frames and 213 low-quality frames (Table 1). Areas A and B had similar
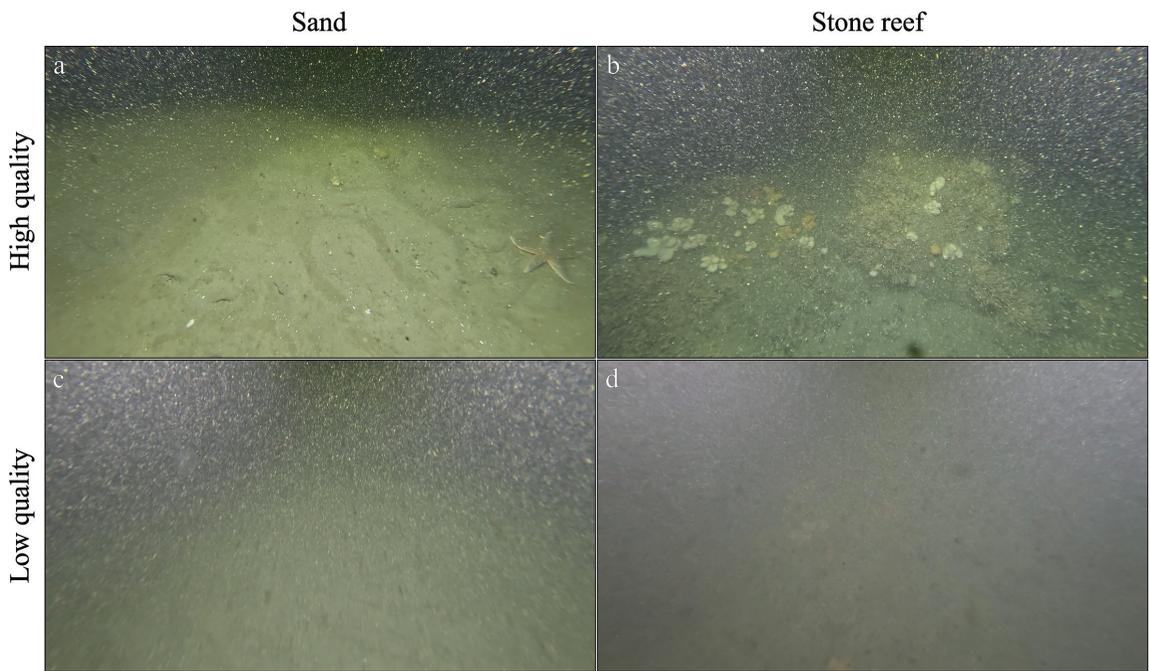
Figure 3: Example of high- and low-quality frames in the sand (A and C) and stone reef substrate (B and D). A) and B) are high-quality frames in the sand and stone reef substrate, respectively. C) and D) are low-quality frames in sand and stone reef substrate, respectively.

frames (412 and 413 frames), while Area C had fewer frames (151 frames). The quality of frames differed between areas: Area A had 338 high-quality frames and 74 low-quality frames, whereas Areas B and C had almost one-third of their frames categorized as low-quality (127 low-quality frames for Area B and 69 low-quality frames for Area C) (Figure 3).

3.3 Classification of Substrate Type

Sand was the most abundant substrate, observed in all areas and sites (representing 513 out of 976 frames and 85.5 minutes) (Table 1, Figure 3). Stone reef substrate was observed in all areas but only in five sites (Sites 1, 7, 8, 9, and 10), accounting for a total of 327 frames. The higher number of sand frames compared to stone reef frames is not due to a higher quality of frames in the sand substrate but because sand was the dominant substrate in the entire study area, while stone reefs occurred in patches. Classifying stone reef substrate was

easier than sand substrate in murky water (dark or cloudy water), as the stone reef structure and the fauna's colour contrasted with the water. The sand substrate was less apparent in murky water and primarily classified based on ripples.

Of the 213 low-quality frames, 136 were labelled "not identifiable" (Table 1) as the substrate could not be determined. These frames were not allocated to a single site but were found in nine of the 12 sites. The three sites with no "not identifiable" frames were all in Area A (Table 1), which had an overall higher visibility. Area B had 86 frames labelled "not identifiable," with 58 of these frames from a single site (Site 5). Similarly, Area C had one site (Site 10) accounting for half of the area's "not identifiable" frames (26 out of 44 frames).

3.4 Detection and Identification of Taxa

Out of the 763 frames classified as high-quality with identified substrates, 73 frames contained
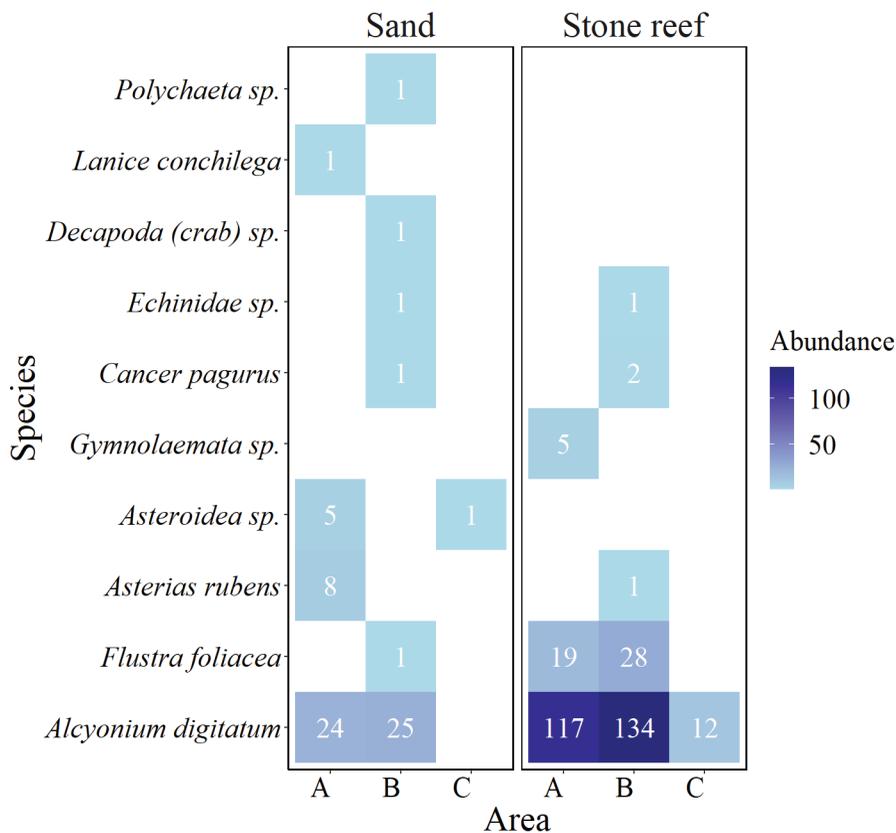
Figure 4: Taxa abundance per area and substrate type. The number of cells indicates the abundance. Cells without colour or number indicate that taxa were not present. Taxa name ending with sp. informs that taxon was not classified to species level.

detectable organisms (see all frames at https://www.kaggle.com/amandairlind/datasets). Taxa were observed in all three areas and in nine out of the 12 sites (except for sites 3, 5, and 12). No detectable organisms were found in five sand sites (Sites 3, 5, 9, 10, and 12), while organisms were observed at all stone reef sites, though not in every frame. Area C had a lower abundance than Areas A and B, with only 13 individuals detected in Area C. One soft coral species, dead man's fingers (*Alcyonium digitatum*), accounts for 12 of the 13 individuals. Area A had six taxa, while Area B had the highest richness with seven taxa.

A total of 10 unique taxa were detected. Of these, nine were found in the sandy substrate,

and six of the 10 taxa were found in the stone reef substrate (Figure 4). The abundance differed greatly, with 69 individuals detected in the sand substrate, while the stone reef substrate had an abundance four times higher (319 individuals). The abundance in the sand and stone reef substrates was dominated by *A. digitatum* (59 individuals in sand and 263 individuals in stone reef). Stone reef substrates also had a high abundance of Bryzoan (*flustra foliacea* and *gymnolaemata*) while one Bryzoan was observed in sand. In the sand substrate, two worm taxa were observed (polychaete sp. and *Lanice conchilega*).

The quality of frames, particularly the resolution, affected the detectability of sizes.

All individuals were categorized as macrofauna (retained by >1 mm mesh) and epifauna, except for the worm taxa (infauna). The frame resolution also affected the taxonomic resolution, with only five of 10 taxa classified at the species level.

4. DISCUSSION

4.1 Effectiveness of Low-Cost ROV

In this study, we tested the monitoring potential of a low-cost ROV in various areas and substrates subject to turbidity and strong currents. The ROV performed well at depths from 15-34 m. Given that models like ours have a depth rating to 200 m, it is expected that it can provide data at greater depths, though potentially limited in battery capacity. Compared to other monitoring tools, such as seabed towed camera systems, grabs, and sledges, which are limited to soft-bottom substrates, the ROV functioned well in both sand and stone reef substrates. Considering the ROV's versatility, it is expected to function in other substrates such as mussel beds, muddy areas, and eelgrass beds. The ROV's easy manoeuvring and live video feed help avoid collisions, which is especially important in eelgrass beds, where the thruster could become entangled in the leaves and cause damage to both the eelgrass bed and the ROV.

Compared to seabed-towed or larger camera systems and scientific ROVs, small eyeball class ROVs are easy to use, require little training, and can be deployed from smaller vessels or even from the coast in coastal shallow areas where a vessel cannot be used. Smaller drop cameras can, in many aspects, be used similarly to the small ROV; however, the drop cameras are less flexible to instantly adjust heading and rely on drifting to cover the same area as the ROV.

4.2 Monitoring Capabilities – Substrate Classification and Species Identification

The greatest challenge encountered in this study and with underwater cameras, in general, is the occurrence of colour distortions because red wavelengths are absorbed faster than the blue and green, which reduces the visible colours [30]. Other challenges are the environmental factors such as murky water and organic matter in the water column (marine snow) and strong currents, which reduce frame quality [13], [31], [32]. These conditions are common in most marine habitats, especially in depths from 0 to 100 metres. Coincidentally, such areas require extensive monitoring due to concentrated human activities (e.g., fishing, sailing, coastal infrastructure), habitat diversity (e.g., stone reef, coral reef, mangroves), and high exposure to pollution and contamination [33].

Environmental factors cannot be controlled; hence, frame quality must be improved by adjusting the camera and floodlight in a position and with a lumen to minimize backscatter from marine snow [13], [34]. Complete avoidance of backscatter in turbid water is not possible, as seen in this study. Therefore, post-processing is essential to improve frame quality. Several post-processing tools have shown promising results in enhancing frame quality [30], [35], [36], [37]. By improving the frame quality, more accurate and detailed information can be extracted [30], [37]. In our study, 14% of the frames were of such low quality that the substrate could not be identified, and organisms could not be

detected in 22% of the frames. Implementing a post-processing tool to remove marine snow and enhance colour will increase the number of frames suitable for substrate and species-level identification, thereby strengthening the ROV's monitoring potential.

Enhanced frame quality could potentially improve the taxonomic resolution [37]. Only 50% of the different taxa could be classified at the species level due to issues such as organisms being too small, cryptic, or partially obscured in complex structural habitats (e.g., Bryzoan in stone reefs) to be accurately identified from frames alone [14], [31], [32]. This limitation is common to all camera systems but not a problem for sampling equipment such as grabs, survey trawls, and sledges, which collect specimens, allowing for species-level classification. These sampling methods also enable the sampling of smaller and infauna species that are not visible with low-cost ROVs. However, these issues are not unique to small, low-cost ROVs, as even industry cameras are unable to penetrate the sediment and observe infauna.

Manual data processing is time-consuming and laborious. Annotation protocol [32], [38] and automated recognition or analysis models have been successfully developed for other ecosystems to determine spatial cover (e.g., of stone reefs) [39], identify taxa [40], [41], and highlight salient objects [42]. These models require a strong ground truth to be effective. No models have been specially designed for our environment, but existing models can be modified and trained on our data, thereby increasing the efficiency and replicability of

annotation and monitoring capabilities. Our data allowed us to determine taxa richness and abundance, but overcoming the challenges and limiting the laborious task will enhance the effectiveness of ROVs in marine monitoring.

4.3 Ecological Information
The difference in macrofauna composition between the sand and stone substrate is primarily due to the substrate itself. Bryzoans and dead man's finger, which dominate in stone reefs, require hard surfaces to attach to. This explains their lower abundance in sand substrates, where these taxa were only observed if hard substrates were present, such as smaller stones. As a result of these two taxa, the abundance was higher in stone reefs compared to the sand substrates. Despite that they cover a smaller proportion of the seabed than the sandy substrate, as seen in our study, they are ecologically important as they provide substrate and shelter for a variety of species [43], [44].

Counting dead man's fingers and Bryzoans as individuals can be problematic because they have multiple branches, overlap with each other, or are layered. Therefore, determining these species in terms of biomass would be more informative. Biomass determination can be achieved by mounting a laser pointer on the ROV (Figure 2b), which allows for measuring the size of organisms or spatial coverage [45]. Size can be correlated with biomass and used to estimate age. This method can also be applied to other species to determine their size and biomass. Furthermore, data can be converted into biodiversity measures or coupled with traits and functionality to provide ecological information about the ecosystem.

4.4 Future Work

ROVs are effective and versatile monitoring tools, but several challenges must be addressed to maximize their potential. The most important improvement needed is the frame quality to enhance the accuracy of the data. This can be achieved by adjusting the system itself or enhancing quality through post-processing. For ROVs to be widely adopted in monitoring programs, post-processing tools must be approachable to individuals with varying professional backgrounds.

Improving frame quality can enhance species identification, which is currently challenging due to morphological similarities and motion blur that limit the ability to identify at the species level. However, some species are morphologically similar and can only be distinguished by having a physical specimen or DNA samples. Combining camera observations with eDNA can provide the final information at the species level and additional information on species present in the environment that might not have been observed. eDNA samples can be taken simultaneously with the ROV's recordings by mounting a filter that collects particles in the water or a water/sediment sampler.

Additionally, higher resolution on the camera is needed to enable the detection of smaller organisms. To demonstrate the ROV's versatility, further studies in various substrates, depths, and marine environments are needed to ensure replicability and to streamline the sampling method.

5. CONCLUSION

Our study demonstrated the effectiveness of a low-cost ROV for monitoring two marine substrates in low visibility due to turbid and murky water. Enhancing the image quality could improve organism detection and taxa classification, and methods are needed to make versatile and replicable ecological assessments. This study provides essential information that can be used in a management context regarding substrates, species composition, biodiversity, and seabed state.

ACKNOWLEDGMENT

REFERENCES

[1]   H. Frigstad *et al*., Andersen, H. Trannum, M. McGovern, L. Naustvoll, O. Kaste, A. Deininger og D. Hjermann, "Three decades of change in the Skagerrak coastal ecosystem, shaped by eutrophication and coastal darking," *Estuarine, Coastal, and Shelf Sci*., vol. 283, p. 108193, 2023, doi: 10.1016/j.ecss.2022.108193.

[2]   A. Palialexis *et al*., "Monitoring biodiversity for the EU Marine Strategy Framework Directive: Lessons learnt from evaluating the official reports," *Mar. Policy*, vol. 128, p. 104473, 2021, doi: 10.1016/j.marpol.2021.104473.

[3]   European Union, "Directive 2008/56/EC of the European Parliament and of the Council of 17 June 2008 establishing a framework for community

action in the field of marine environmental policy" (Marine Strategy Framework Directive), 2008.

[4] European Union, "Council Directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora," *Official Journal of the European Union*, vol. 206, no. 7, p. 50, 1992.

[5] G. Van Hoey *et al*., "Methodological elements for optimising the spatial monitoring design to support regional benthic ecosystem assessments," *Environ. Monit. Assess*., vol. 191, no. 7, pp. 423-13, 2019, doi: 10.1007/s10661-019-7550-9.

[6] S. Birk *et al*., "Three hundred ways to assess Europe's surface waters: An almost complete overview of biological methods to implement the Water Framework Directive," *Ecological Indicators*, vol. 18, pp. 31-41, 2012, doi: 10.1016/j.ecolind.2011.10.009.

[7] N. Zampoukas *et al*., "Technical guidance on monitoring for the Marine Stategy Framework Directive," 2014.

[8] H. Rumohr, "Soft bottom macrofauna: Collection, treatment, and quality assurance of samples," *ICES Techn. In Mar. Environ. Sci*., no. 43, 2009, doi: 10.25607/OBP-238.

[9] R. Rosenberg and H.C. Nilsson, "Deterioration of soft-bottom benthos along the Swedish Skagerrak coast," *J. Sea Res*., vol. 54, no. 3, pp. 231-242, 2005, doi: 10.1016/j.seares.2005.04.003.

[10] M. Obst *et al*., "Marine long-term biodiversity assessment suggests loss of rare species in the Skagerrak and Kattegat region," *Mar. Biodiv*., vol. 48, no. 4, pp. 2165-2176, 2018, doi: 10.1007/s12526-017-0749-5.

[11] D. Morris, D. Speirs, A. Cameron, M. Heath, "Global sensitivity analysis of an end-to-end marine ecosystem model of the North Sea: Factors affecting the biomass of fish and benthos," *Ecological Model*., vol. 273, pp. 251-263, 2014, doi:10.1016/j.ecolmodel.2013.11.019.

[12] I. Kröncke *et al*., "Changes in North Sea macrofauna communities and species distribution between 1986 and 2000," *Estuarine, Coastal and Shelf Sci.*, vol. 94, no. 1, pp. 1-15, 2011, doi: 10.1016/j.ecss.2011.04.008.

[13] E. Sheehan *et al.*, "An experimental comparison of three towed underwater video systems using species metrics, benthic impact and performance," *Methods in Ecol. and Evol.*, vol. 7, no. 7, pp. 843-852, 2016, doi: 10.1111/2041-210X.12540.

[14] A. Williams, F. Althaus, T. Schlacher, " Towed camera imagery and benthic sled catches provide different views of seamount benthic diversity," *Limnol. and Oceanogr. Methods*, vol. 13, no. 2, pp. 62-73, 2015, doi: 10.1002/lom3.10007.

[15] M. Lacharité and C. Brown, "Utilizing benthic habitat maps to inform biodiversity monitoring in marine protected areas," *Aquatic Conservation*, vol. 29, no. 6, pp. 938-951, 2019, doi: 10.1002/aqc.3074.

[16] S. de Mendonça and A. Mextaxas, "Comparing the performance of a remotely operated vehicle, a drop camera, and a trawl in capturing deep-sea epifaunal abundance and diversity," *Frontiers in Mar. Sci.*, vol. 8, 2021, doi: 10.3389/fmars.2021.631354.

[17] R. Easton, S. Heppell, R. Hannah, "Quantification of habitat and community relationships among nearshore temperate fishes through analysis of drop camera video," *Mar. and Coastal Fisheries*, vol. 7, no. 1, pp. 87-102, 2015, doi:10.1080/19425120.2015.1007184.

[18] N. Bethoney and K. Stokesbury, "Methods for image-based surveys of benthic macroinvertebrates and their habitat exemplified by the drop camera survey for the Atlantic Sea Scallop," *J. Vis. Exper*., vol. 137, 2018, doi: 10.3791/57493.

[19] A. Yusof, M. Nor, M. Aras, S. Shamsudin, "Open-source platform comparison for research and development in underwater drones," *Proceedings of the 12th National Technical Seminar on Unmanned System Technology 2020*, Singapore, 2021, pp. 139-151.

[20] R. Pacunski, W. Palsson, H. Greene, H. Gunderson, "Conducting visual surveys with a small ROV in shallow water," *Marine Habitat Mapping Technology for Alaska*, 2008, pp. 109-128, doi: 10.4027/mhmta.2008.08.

[21] E. Buscher, D. Mathews, C. Bryce, K. Bryce, D. Joseph, N. Ban, "Applying a low cost, mini remotely operated vehicle (ROV) to assess an ecological baseline of an indigenous seascape in Canada," *Frontiers in Mar. Sci*., vol. 7, doi: 10.3389/fmars.2020.00669.

[22] O. Eigaard et al., "The footprint of bottom trawling in European waters: distribution, intensity, and seabed integrity," *ICES J. Mar. Sci*., vol. 74, no. 3, pp. 847-865, 2017, doi: 10.1093/ICESJMS/FSW194.

[23] C. Davies, D. Moss, M. Hill, "EUNIS Habitat Classification Revised 2004," 2004, pp. 127-143.

[24] European Environment Agency. "Habitat types key navigation." EUNIS. Accessed: April 4, 2024. [Online]. Available: https://eunis.eea.europa.eu/habitats-key.jsp

[25] European Environment Agency. "Atlantic circalittoral sand." EUNIS. Accessed: April 4, 2024. [Online]. Available: https://eunis.eea.europa.eu/habitats/31202p

[26] European Environment Agency. "Atlantic circalittoral rock." EUNIS. Accessed: April 4, 2024. [Online]. Available: https://eunis.eea.europa.eu/habitats/30972

[27] H. Wickham, R. François, L. Henry, K. Müller, "*dplyr: A grammar of data manipulation*," R package version 0.4, vol. 3, p. 156, 2015.

[28] H. Wickham et al., "Welcome to the Tidyverse," *J. Open Source Softw.*, vol. 4, no. 43, p. 1686, 2019, doi: 10.21105/JOSS.01686.

[29] H. Wickham, *ggplot2 : Elegant graphics for data analysis*, 1st ed., New York, NY, USA: Springer, 2009.

[30] Y. Wang, W. Song, G. Fortino, L. Qi, W. Zhang, A. Liotta, "An experimental-based review of image enhancement and image restoration methods for underwater imaging," *Access*, vol. 7, pp. 140233-140251, 2019, doi: 10.1109/ACCESS. 2019.2932130.

[31] C. Jac *et al.*, "Assessing the impact of trawling on benthic megafauna: comparative study of video surveys vs. scientific trawling," *ICES J. Mar. Sci.*, vol. 78, no. 5, pp. 1636-1649, 2021, doi: 10.1093/ icesjms/fsab033.

[32] B. Taormina *et al.*, "Optimizing image-based protocol to monitor macroepibenthic communities colonizing artificial structures," *ICES J. Mar. Sci.*, vol. 77, no. 2, pp. 835-845, 2020, doi: 10.1093/ icesjms/fsz249.

[33] R. Seitz, H. Wennhage, U. Bergström, R. Lipcius, T. Ysebaert, "Ecological value of coastal habitats for commercially and ecologically important species," *ICES J. Mar. Sci.*, vol. 71, no. 3, pp. 648-665, 2014, doi: 10.1093/icesjms/fst152.

[34] R. Taylor *et al.*, "Evolution of a benthic imaging system from a towed camera to an automated habitat characterization system," in *OCEANS 2008*, Quebec City, QC, Canada, 2008, pp. 1-7 doi: 10.1109/OCEANS.2008.5152032.

[35] Z. Lyu, A. Peng, D. Wang, D. Ding, "An efficient learning-based method for underwater image enhancement," *Displays*, vol. 74, p. 102174, 2022, doi: 10.1016/j.displa.2022.102174.

[36] B. Cyganek and K. Gongola, "Real-time marine snow noise removal from underwater video sequences," *J. Electron. Imag.*, vol. 27, no. 4, p. 043002, 2018, doi: 10.1117/1.JEI.27.4.043002.

[37] J. Ahn, S. Yasukawa, T. Sonoda, T. Ura, K. Ishii, "Enhancement of deep-sea floor images obtained by an underwater vehicle and its evaluation by crab recognition," *J. Mar. Sci. Technol.*, vol. 22, no. 4, pp. 758-770, 2017, doi: 10.1007/s00773-017-0442-1.

[38] F. Althaus *et al.*, "A standardised vocabulary for identifying benthic biota and substrata from underwater imagery: The CATAMI Classification Scheme," *PloS One*, vol. 10, no. 10, p. e0141039, 2015, doi: 10.1371/journal.pone.0141039.

[39] G. Raber and S. Schill, "A low-cost small unmanned surface vehicle (sUSV) for very high-resolution mapping and monitoring of shallow marine habitats," *Proceedings of Remote Sensing of the Ocean, Coastal Waters, and Large Water Regions*,

vol. 11150, 2019, doi: 10.1117/12.2531361.

[40] M. Ahmed, L. Peña-Castillo, A. Vardy, P. Gagnon, "Improving detection and localization of green sea urchin by adding attention mechanisms in a convolutional network," *J. Ocean Technol.*, vol. 19, no. 2, pp. 82-97, 2024. [Online]. Available: www.thejot. net/article-preview/?show_article_preview=1532

[41] M. Pedersen, J. Bruslund Haurum, R. Gade, T. Moeslund, N. Madsen, "Detection of marine animals in a new underwater dataset with varying visibility," in *Proc. of the IEEE/CVF Conf. on Comput. Vis and Pattern Recognit. (CVPR) Workshops*, Long Beach, California, USA, Jun. 2019, pp. 18-26.

[42] N. Kumar, H. Sardana, S. Shome, N. Mittal, "Saliency subtraction inspired automated event detection in underwater environments," *Cogn. Comput.*, vol. 12, no. 1, pp. 115-127, 2020, doi: 10.1007/s12559-019-09671-x.

[43] C. Stenberg, *et al.*, "Ecological benefits from restoring a marine cavernous boulder reef in Kattegat, Denmark," DTU Aqua Rep., vol. 49, 2015.

[44] J. Svendsen et al., "The importance of reef habitats for fish, harbor porpoise and fisheries management," *DTU Aqua Rep.*, vol. 82, 2020.

[45] F. Dias *et al.*, "Area estimation of deep-sea surfaces from oblique still images," *PloS One*, vol. 10, no. 7, p. e0133290, 2015, doi: 10.1371/journal.pone. 0133290.