An Acoustic and Optical Dataset for the Perception of Underwater Unexploded Ordnance (UXO)

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***Abstract*—During the 20st century, millions of tons of munition were dumped into the oceans worldwide. After decades of decay, the problems these unexploded ordnance (UXO) are causing are starting to become apparent. In order to facilitate more efficient salvage efforts through e.g. autonomous underwater vehicles, access to representative data is paramount. However, so far such data is not publicly available. In this paper we present a dataset of multimodal synchronized data for acoustic and optical sensing of UXO underwater. Using an ARIS 3000 imaging sonar, a GoPro Hero 8 and a custom design gantry crane, we recorded close to 100 trajectories and over 74,000 frames of 3 distinct types of UXO in a controlled environment. Included in this dataset are raw and polar transformed sonar frames, annotated camera frames, sonar and target poses, textured 3D models, calibration matrices, and more. The dataset is publicly available at https://zenodo.org/records/11068046. The code for processing the raw data is available at https://github.com/dfki-ric/uxo-dataset2024.**

I. Introduction

Wars often leave countries riddled with unexploded ordnance (UXO) in the form of both duds and stocks beyond the peacetime reserves. Maintaining or properly recycling this surplus is costly and inefficient. The common policy of previous decades was therefore to dump the no longer required munitions into the oceans. In the German oceans alone, an estimated 1.6 *million* tons lie dormant at the bottom of the sea [1]. As the objects slowly rot away, UXO can become unstable or release toxic agents into the environment, affecting habitats and food chains [2]. These problems are not new; however, with the growing interest in environmental protection [3], [4] and marine infrastructure [5], policies are now shifting towards recovery and disposal of munitions without disturbing the environment whenever possible [6], [7]. An increase in munitions clearance operations at sea can be expected in the near future.

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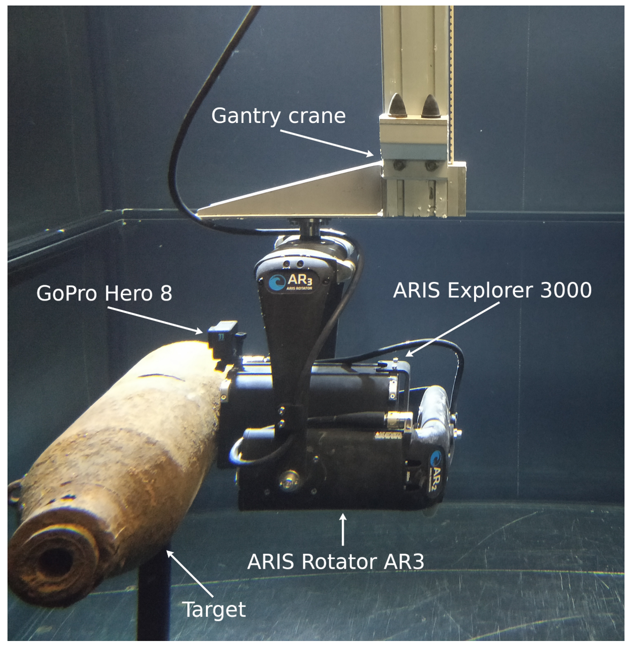

Fig. 1. Experiment setup in the test basin at DFKI RIC, Bremen, Germany.

UXO are usually handled by explosive ordnance disposal (EOD) experts, who decide whether an UXO is safe to transport, safe to handle, or has to be destroyed in situ [8]. Important risk factors are the munition type, its overall condition, and the state of its fuse [9].

In air, this assessment could be mostly made by visual inspection. However, due to limited amounts of natural light and turbidity, visibility underwater tends to be limited and a major factor preventing UXO identification [10]. Turbidity can be particularly high near river estuaries, after storm events [11], and in harbor areas [12]. This is also true for underwater work in general, and EOD operations in particular, as they often lead to the mobilisation of sediments. For example, during EOD, uncovering UXO by underwater jetting is discouraged because they strongly disperse sediment even with suction equipment [13], [14]. Lower visibility also impairs the actual handling procedures, be it salvaging, underwater transfer, or in situ destruction.

For initial localization and to get a first impression, EOD experts have started using high-frequency sonars with large

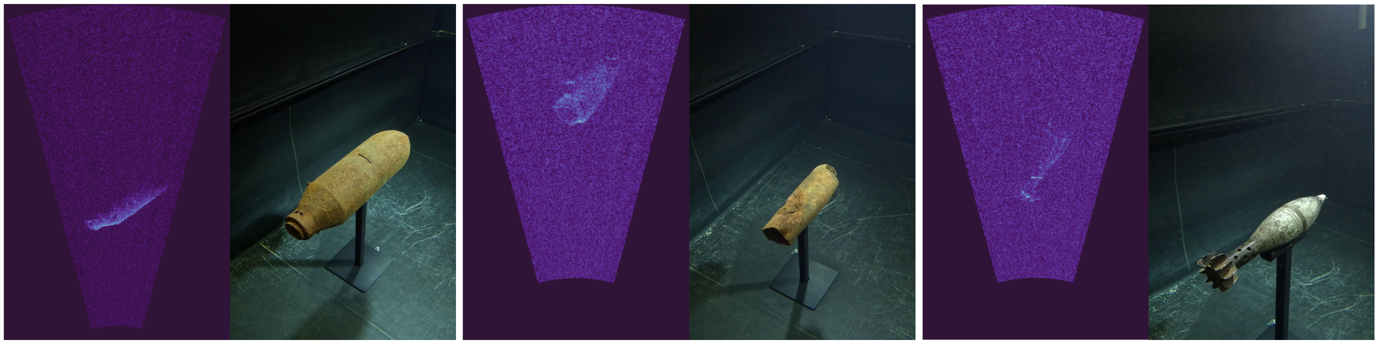

Fig. 2. Matched sonar and camera frames. From left to right: 100lb GP AN-M30, Phosphor bomb INC 30lb MK III, 120mm Mortar bomb DM81.

TABLE I
DIMENSIONS AND TYPES OF RECORDED UXO OBJECTS

	US Bomb 100lb GP AN-M30	Phosphor bomb INC 30lb Mk III	120mm Mortar bomb DM81
Condition	Heavily rusted	Heavily rusted and deformed	Good
Length	737 mm	442 mm	580 mm
Diameter	208 mm	127 mm	120 mm
Weight	51 kg	11.3 kg	12.8 kg

vertical apertures [7] like the ARIS Explorer 3000 for acoustic imaging. The successful application of this sensor for EOD has been reported both for experimental set-ups [15], and in production [16]. However, sonars struggle to penetrate the sediment for more than a few centimeters and are often difficult to interpret by humans. EOD divers therefore still rely on haptic feedback for their assessment [7], [14]. In a profession that is already hazardous, this method of object identification obviously constitutes a particularly high-risk activity.

Chemical sensing has also been proposed for UXO localization by collecting water samples through divers [10] or Niskin bottles [17]. However, due to the huge variety and diverse material compositions, chemical sensing cannot provide information on the munition type or state of the fuse of an object.

One idea to support UXO identification and alleviate risks to EOD divers is to use artificial intelligence (AI) to discover features where humans are struggling [18], [19]. In recent years, AI has particularly excelled in environmental perception, notably in camera-based image understanding such as object identification and classification.

However, a problem most of today's AI algorithms are facing is the large amount of data required to train a model, often consisting of millions of images for general vision based tasks [20]. While general object recognition models can be used as a basis for more specific recognition tasks, this specialization typically still requires hundreds to thousands of images [21]. Variations in lighting conditions can further exacerbate this issue [22]. The domain of underwater UXO is particularly affected by this scarcity; no high-quality dataset has been published thus far. The topic is inherently sensitive due to security concerns, and most of the data is acquired by private companies and not made available to the public, which impedes research in this area. Additionally, in-situ data often lacks critical information, like the type and state of scanned objects, object pose information, coverage gaps [23], etc.

This issue can be solved to some degree by employing generative AI methods, e.g. generative adversarial networks (GANs) to generate fake data resembling a reference dataset [24], [25]. Conditional GANs, for instance, have been employed to generate camera-like images from acoustic information sourced from imaging sonars or multibeam echosounders in low visibility underwater environments [26], [27]. However, a reference dataset is still required to guide generation in the right direction. On one hand, this approach can enhance the available dataset by introducing more variability. On the other hand, it is of course limited by what is included in the reference dataset and can therefore never cover features not already present.

AI models have also been used in more specialized scenarios like underwater robots [28]. Current work at DFKI focuses on developing and adapting methods for combined 3D reconstruction and pose estimation of UXO. The goal is to enable an intervention AUVs like the underwater robot *Cuttlefish* [29] to locate, identify, and prepare UXO for EOD.

In summary, visual inspection is not always possible, and methods to obtain additional information are either very risky for humans or insufficient for UXO identification. To lower the risk for humans and extend handling capabilities, the use of AI models and intervention AUVs seems opportune, yet is hindered by the availability of usable training data.

To facilitate further research, we created a dataset of acoustic and optical scans of UXO underwater, recorded in a controlled experimental environment. It has the following properties:

- Sonar scans of multiple UXO using an ARIS Explorer 3000 imaging sonar.
- Matched GoPro UHD frames for most sonar frames.
- Known and accurate transforms between sonar and targets.
- Known details UXO targets including munition types, dimensions, and 3D models.
- Tracked scan trajectories that are typical and achievable for non-experimental environments.
- Publicly available at https://zenodo.org/records/11068046.
- Export scripts available at https://github.com/dfki-ric/uxo-dataset2024.

II. Related Datasets

Since many off-shore dumping sites were not properly documented, the first challenge for recovery and disposal is localization. This usually involves ships equipped with mutlibeam echosounders (MBES) and sidescan sonars (SSS). Collecting this kind of data has been standard practice over many years for any kind of seafloor construction. However, these recordings are usually considered sensitive, as they cover critical infrastructure sites and company secrets. UXO can also be recovered for nefarious means and pose a high risk for civilians [30]. As a result, most of this data is not publicly disclosed [31].

Even if these datasets were made public, their usefulness for e.g. EOD divers would be limited due to the limited amount of information that can be collected from a sonar survey. Known problems include limited resolution, fixed viewing angles, digital elevation models (DEM) instead of 3D models, and missing information on detected objects.

Brown et al. [32] have circumvented this issue in their Synthethic Aperture Sonar (SAS) dataset by generating sensor data both from physics simulations and recordings of a prepared test site. This dataset has a strong focus on buried or otherwise covered UXO.

Singh et al. [33] provide a forward looking sonar (FLS) dataset with marine debris as targets. For target detection they used Faster-RCNN [34] and YOLOv3 [35] successfully. Ge et al. [36] developed a method based on YOLOv7 and applied it to the same dataset.

Similar datasets exists for the purpose of identifying fish [37] or targets like cylinders and tires [38]. While perfectly suited for sonar semantic segmentation, the lack of navigation data and viewing angles limits their usability for our purposes.

III. Dataset Generation

A. Enviroment and Equipment

Our UXO targets were recorded using an imaging sonar and a camera, both mounted on a pan-tilt unit (PTU) attached to a gantry crane. In particular, the following hardware was used:

- **Sonar**: SoundMetrics ARIS Explorer 3000
- **PTU**: SoundMetrics ARIS Rotator AR3
- **Camera**: GoPro Hero 8 (5.3k UHD)
- **Gantry crane**: custom built

The recordings were collected at the German Research Center for Artificial Intelligence (DFKI) in Bremen, Germany, in a test basin containing 20,000 L of freshwater and measuring 3.4 m x 2.6 m x 2.5 m. The basin is equipped with a gantry crane, which can move freely in the xyz-axes and execute pre-programmed trajectories with sub-millimeter precision at an update rate of 10 Hz, thus allowing for precise repetition of trajectories and recording of positioning ground truths. A PTU was mounted on the gantry crane to hold the sensors, allowing them to rotate freely. Fig. 1 depicts the complete setup used for our recordings.

B. Targets

The recorded targets, shown in Fig. 3, are real UXO objects provided by Eggers Kampfmittelbergung GmbH. Any warfare agents were previously professionally removed. To cover some variety in size and shape, we selected three targets for the recordings: a rusted 100 lb general purpose bomb, a heavily deformed phosphor bomb, and a mortar bomb with a propellant charge case and tail fins. Table I lists their dimensions and exact types. We also took several recordings of a test cylinder for reference.

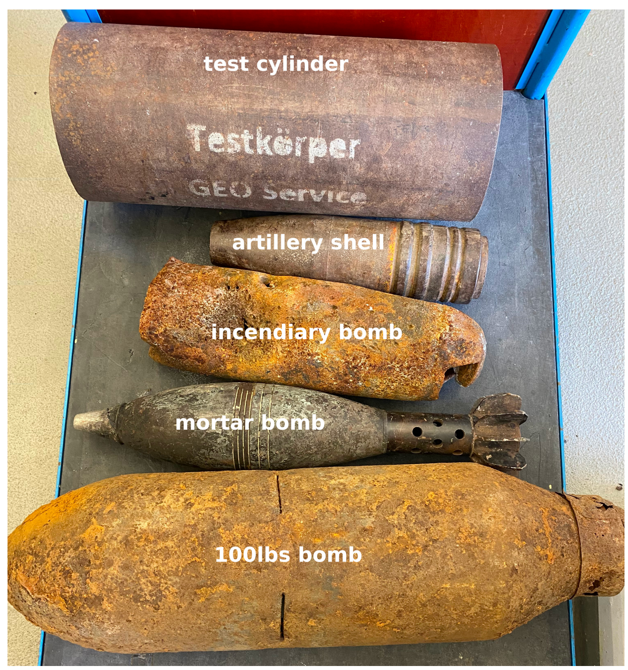

Fig. 3. The UXO targets available for our recordings.

C. Recordings

In total, the dataset includes 95 recordings and 74,437 sonar frames with attached poses and calibration matrices. All data is paired with the type of object, sonar pose, object pose, and sonar parameters like gain and range, etc. For 48,462 of these we also provide camera frames, most of which have annotations in the form labeled bounding boxes. Matching between sonar and camera frames was manually verified. The sonar data is available in three different formats: point clouds, raw images, and polar-transformed images. Additionally, we created and provide a program for viewing the recordings and metadata in a synchronized manner.

The recordings mainly consist of half-orbit trajectories at three different depths. For some configurations, we also conducted linear flyovers at two different angles. The latter are intended to mimic the perspective typically achieved when scanning larger areas for UXO. In order to keep our recordings consistent and improve the signal-to-noise ratio against the background, the targets were mounted on a narrow stand. However, we also recorded complete 360° scans at two different depths for the US Bomb 100lb GP AN-M30 placed on the ground.

During the execution of half- and full-orbit trajectories, pitch and roll were fixed, while the yaw was controlled manually to keep the target in frame. The trajectory was not a perfect circle due to space limitations in the basin. Sonar settings were selected to cover different ranges, gains, and resolutions while still avoiding reflections. We also reconstructed high-fidelity textured 3D models using Agisoft Metashape from more than 150 images per target, recorded in-air with a Canon EOS 80D. The textured 3D models and processing scripts are released alongside the dataset.

D. Data Processing

Our focus for this dataset was on collecting accurately tracked sonar footage. Collecting camera footage was therefore more of an afterthought, albeit a valuable one. However, our decision to use a GoPro resulted in significant overhead in the post processing. There were several issues contributing to this:

- We let the GoPro record continuously over multiple recording instances/trajectories.
- The GoPro's internal clock was not properly synchronized with the rest of our setup.
- GoPro and ARIS recorded data unsynchronized and with different frame rates.
- The transform between GoPro and ARIS was not fixed and slightly moved each battery change.
- Due to low battery, some recordings don't have GoPro footage.

When matching the footage, we found that the GoPro's audio track captured easily identifiable features whenever the crane's motors were engaged, helping us split the footage into one clip per trajectory. Solving the timing issues proved more challenging, and was ultimately done by hand based on visual movement and changes in the optical flow. Since the GoPro recorded at a higher frame rate than the ARIS (30 Hz vs. 15 Hz), we could always select a closest camera frame for each sonar frame. However, even with the use of a custom tool (also part of our release, see fig. 4), this took a considerable amount of time.

In the end, we processed our recordings as follows: 1. extract sonar frames, 2. split camera footage, 3. extract relevant sections, 4. calculate optical flows, 5. match data to sonar frames, 6. export and organize.

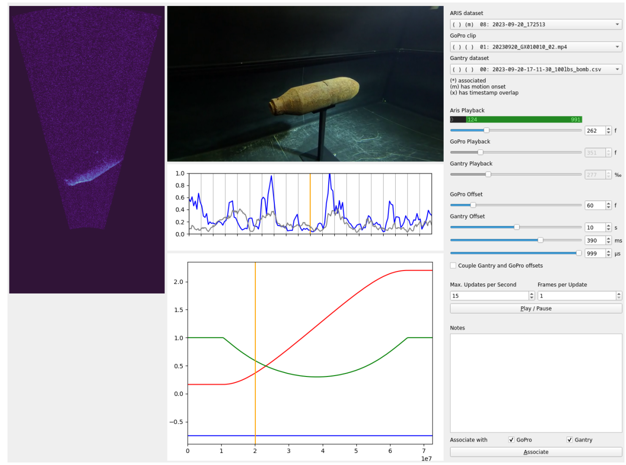

Fig. 4. Matching tool used for aligning sonar and camera recordings.

Almost all scripts are written in Python 3, the remainder is written in Bash. Further details can be found in the code release, available at https://github.com/dfki-ric/uxo-dataset2024.

E. Structure

```
/
├── 3d_models
├── calibration
└── recordings
    └── ${uxo_type}
        └── ${datetime}
            ├── aris_raw
            │   └── ${frame_idx}.pgm
            ├── aris_polar
            │   └── ${frame_idx}.png
            ├── gopro
            │   └── ${frame_idx}.jpg
            ├── label
            │   └── ${frame_idx}.json
            ├── aris_file_meta.yaml
            ├── aris_frame_meta.csv
            ├── gantry.csv
            └── notes.txt
```

Fig. 5. Directory structure of our dataset.

Our recordings are grouped by UXO type first, and then recording timestamp, as shown in Fig. 5. Each recording contains the following:

- *sonar_raw* folder, containing raw sonar frames in .pgm format named by sonar frame index.
- *sonar_polar* folder, containing polar transformed sonar frames in .png format named by sonar frame index (downloaded separately).
- *gopro* folder, containing camera frames in .jpg format named by sonar frame index.
- *label* folder, containing camera frame bounding boxes in .json format named by sonar frame index.

- *aris_file_meta.yaml* file, the sonar metadata.
- *aris_frame_meta.csv* file, the metadata for each sonar frame including PTU angles, indexed by frame number.
- *gantry.csv* file, the gantry crane positions for each sonar frame index.
- *notes.txt* file, containing a short description of the recording and additional notes and comments.

The 3D models are exported as .obj Wavefront files and come along a .mtl material file and the texture in JPEG format.

The calibration folder contains the transforms between the crane and sensors, provided as a .yaml file, and GoPro camera calibrations. A jupyter notebook showing how the transforms can be used using the *transforms3d* package is included in the code release.

F. Annotations

The camera frames were systematically annotated with bounding boxes and object types to facilitate the training of object detection models. This was done automatically where possible, and by hand using *Make Sense* [39] for the remaining frames. The automated annotation involved the following steps:

- **Image Conversion**: Conversion from BGR to HSV color space to enable better color-based segmentation.
- **Mask Creation**: Identify HSV ranges that isolate the UXO well.
- **Thresholding and Contour Extraction**: Combination of mask with contour detection to exclude stray sections.
- **Bounding Box Extraction**: Mapping of isolated regions to bounding boxes.

In total, we provide 37,278 annotated images. The distribution of data per class is presented in Table II. Frames from e.g. the test cylinder was not labeled.

TABLE II
NUMBER OF SAMPLES PER CLASS

Class	Number of samples
100lbs_aircraft_bomb	15,536
incendiary_grenade	9,157
mortar_shell	12,585

IV. CONCLUSION

We find that research on AI models for underwater UXO detection, identification and autonomous handling through e.g. intervention AUVs is hindered by the near non-existent availability of public datasets. We aim to make a contribution by providing a publicly available dataset of three different UXO types, using a high frequency imaging sonar, a high resolution camera and a remote controlled gantry crane. The dataset includes UXO and sensor poses, time-matched frames, annotations, textured 3D models, calibrations, and the scripts we used for processing the data. We hope that this dataset will be useful in future research for solving a major problem inherited from the past: the recovery and disposal of unexploded ordnance that have been dumped into the oceans.

A. Lessons Learned

Collecting our dataset did not come without hassles. For those readers planning to record a dataset on their own, these are our major takeaways:

- All sensor data should be collected by one central entity. Exceptions to this are not worth the resulting overhead in post-processing.
- Sensors that can't be integrated this way should be replaced. Establishing strict procedures for sensors outside this setup helps with consistency.
- Keep processing times in mind. UHD footage may sound appealing, but is difficult to work with.
- Schedule time in between recordings for validation.
- Check the state of battery powered sensors before each recording.
- Make sure you have well-defined transforms between your sensors.

B. Future Work

Our motivation to record this dataset lies in the following research goals:

- To train AI models for feature and pose estimation of UXO.
- To develop algorithms for 3D reconstruction from acoustic data.
- To inform interaction strategies for intervention AUVs to support UXO recovery.

The outcomes of these research goals will be presented in more detail in future papers.

REFERENCES

[1] A. Bach, C. Böttcher, A. Jaser, T. Knobloch, J. Sternheim, I. Weinberg, U. Wichert, and J. Wöhler, *Munitionsbelastung der Deutschen Meeresgewässer - Entwicklungen und Fortschritt (2019 & 2020)*. Kiel: Ministerium für Energiewende, Klimaschutz, Umwelt und Natur, Dec 2023. [Online]. Available: https://www.munition-im-meer.de

[2] E. Maser and J. S. Strehse, ""don't blast": blast-in-place (bip) operations of dumped world war munitions in the oceans significantly increase hazards to the environment and the human seafood consumer," *Archives of Toxicology*, vol. 94, no. 6, pp. 1941–1953, 2020.

[3] A. M. von Benda-Beckmann, G. Aarts, H. Ö. Sertlek, K. Lucke, W. C. Verboom, R. A. Kastelein, D. R. Ketten, R. van Bemmelen, F.-P. A. Lam, R. J. Kirkwood, and M. A. Ainslie, "Assessing the impact of underwater clearance of unexploded ordnance on harbour porpoises (phocoena phocoena) in the southern north sea," *Aquatic Mammals*, vol. 41, no. 4, pp. 503–523, 2015.

[4] U. Siebert, J. Stürznickel, T. Schaffeld, R. Oheim, T. Rolvien, E. Prenger-Berninghoff, P. Wohlsein, J. Lakemeyer, S. Rohner, L. Aroha Schick, S. Gross, D. Nachtsheim, C. Ewers, P. Becher, M. Amling, and M. Morell, "Blast injury on harbour porpoises (phocoena phocoena) from the baltic sea after explosions of deposits of world war ii ammunition," *Environment international*, vol. 159, p. 107014, 2022.

[5] Z. Liu, R. Igland, S. Bruaseth, L. Ercoli-Malacari, and O. A. Lillebø, "A design practice for subsea pipeline subjected to uxo hazards," in *Proceedings of the ASME 38th International Conference on Ocean, Offshore and Arctic Engineering - 2019*. New York, N.Y.: The American Society of Mechanical Engineers, 2019.

[6] W. Sichermann, T. Frey, W. Hesse, and J. Greinert, "Kriterien und auswahl der erprobungsgebiete, machbarkeitsstudie und koordinationsvorhaben zum sofortprogramm munitionsaltlasten in nord- und ostsee."

[7] T. Frey, *Quality Guideline for Offshore Explosive Ordnance Disposal*, 1st ed. Berlin, Zurich, Vienna: Beuth Verlag GmbH, 2020.

[8] Deutsche Gesetzliche Unfallversicherung e.V., “Handlungsanleitung zur gefährdungsbeurteilung und festlegung von schutzmaßnahmen bei der kampfmittelräumung,” Berlin, 2020. [Online]. Available: https://tinyurl.com/4bpyf5j5

[9] T. Frey, “Uxo and environmental risk factors impacting eod operations in german waters**,” *Propellants, Explosives, Pyrotechnics*, vol. 49, no. 4, 2024.

[10] P. J. Rodacy, S. D. Reber, and P. K. Walker, “Chemical sensing of explosive targets in the bedford basin, halifax, nova scotia,” Albuquerque (NM) and Livermore (CA). [Online]. Available: https://tinyurl.com/p55wmpxm

[11] M. J. DeWeerts, “Detection of underwater military munitions by a synoptic airborne multi-sensor system,” Honolulu (HI). [Online]. Available: https://tinyurl.com/2p953s98

[12] D. G. Gallagher, “Diver-based rapid response capability for maritime-port security operations,” in *OCEANS’11 MTS/IEEE KONA*, 2011, pp. 1–10. [Online]. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6106892

[13] S. Koschinski and K. Kock, “Underwater unexploded ordnance - methods for a cetacean-friendly removal of explosives as alternatives to blasting,” Nehmten and Hamburg. [Online]. Available: https://tinyurl.com/ky2b6w2c

[14] Arbeitskreis Arbeitshilfen Kampfmittelräumung, “Baufachliche richtlinien kampfmittelräumung (bfr kmr), arbeitshilfen zur erkundung, planung und räumung von kampfmitteln auf liegenschaften des bundes,” Berlin and Bonn. [Online]. Available: https://tinyurl.com/ctm9wmnv

[15] S. J. Schmit, “Cut and capture system technology for demilitarization of underwater munitions,” Elk River (MN). [Online]. Available: https://tinyurl.com/m8amycxs

[16] “Abschlussbericht kampfmittelräumung minsener oog,” Wandlitz.

[17] J. Greinert, Ed., *Practical Guide for Environmental Monitoring of Conventional Munitions in the Seas, Results from the BMBF funded project UDEMM “Umweltmonitoring für die Delaboration von Munition im Meer”*, version 1.1 ed., ser. GEOMAR Report, Kiel, 2019, vol. N. Ser. 054.

[18] S. Cho, J. Ma, and O. A. Yakimenko, “Aerial multi-spectral ai-based detection system for unexploded ordnance,” *Defence Technology*, vol. 27, p. 24–37, Sep. 2023. [Online]. Available: http://dx.doi.org/10.1016/j.dt.2022.12.002

[19] M. Kampmeier, P. Michaelis, D. Wehner, T. Frey, M. Seidel, J. Wendt, and J. Greinert, “Workflow towards autonomous and semi-automized uxo survey and detection,” in *6th Underwater Acoustics Conference and Exhibition*. ASA, 2021. [Online]. Available: http://dx.doi.org/10.1121/2.0001492

[20] L. Liu, W. Ouyang, X. Wang, P. Fieguth, J. Chen, X. Liu, and M. Pietikäinen, “Deep learning for generic object detection: A survey,” 2018. [Online]. Available: https://arxiv.org/abs/1809.02165

[21] G. Li, Z. Song, and Q. Fu, “A new method of image detection for small datasets under the framework of yolo network,” in *2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2018, pp. 1031–1035.

[22] K. Sivaraman and A. Murthy, “Object recognition under lighting variations using pre-trained networks,” in *2018 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, 2018, pp. 1–7.

[23] T. Guerneve, K. Subr, and Y. Petillot, “Three–dimensional reconstruction of underwater objects using wide–aperture imaging sonar,” *Journal of Field Robotics*, vol. 35, no. 6, pp. 890–905, 2018.

[24] F. C. Nogues, A. Huie, and S. Dasgupta, “Object detection using domain randomization and generative adversarial refinement of synthetic images,” 2018. [Online]. Available: https://arxiv.org/abs/1805.11778

[25] J. Tobin, R. Fong, A. Ray, J. Schneider, W. Zaremba, and P. Abbeel, “Domain randomization for transferring deep neural networks from simulation to the real world,” in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2017, pp. 23–30.

[26] B. Wehbe, N. Shah, M. Bande, and C. Backe, “Sonar-to-rgb image translation for diver monitoring in poor visibility environments,” in *OCEANS 2022, Hampton Roads*. IEEE, 2022, pp. 1–9.

[27] N. Jaber, B. Wehbe, and F. Kirchner, “Sonar2depth: Acoustic-based 3d reconstruction using cgans,” in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2023, pp. 5828–5835.

[28] L. Christensen, J. de Gea Fernández, M. Hildebrandt, C. E. S. Koch, and B. Wehbe, “Recent advances in ai for navigation and control of underwater robots,” *Current Robotics Reports*, vol. 3, no. 4, pp. 165–175, 2022.

[29] L. Christensen, J. Hilljegerdes, M. Zipper, A. Kolesnikov, B. Hülsen, C. E. S. Koch, M. Hildebrandt, and L. C. Danter, “The hydrobatic dual-arm intervention auv cuttlefish,” in *OCEANS 2022, Hampton Roads*. IEEE, 2022, pp. 1–8.

[30] B. S. Levy, *From Horror to Hope: Recognizing and Preventing the Health Impacts of War*. New York, NY: Oxford University Press, May 2022.

[31] M. Kampmeier, E. M. van der Lee, U. Wichert, and J. Greinert, “Exploration of the munition dumpsite kolberger heide in kiel bay, germany: Example for a standardised hydroacoustic and optic monitoring approach,” *Continental Shelf Research*, vol. 198, p. 104108, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0278434320300649

[32] D. C. Brown, S. F. Johnson, I. D. Gerg, and C. F. Brownstead, “Simulation and testing results for a sub-bottom imaging sonar,” *Proceedings of Meetings on Acoustics*, vol. 36, no. 1, p. 070001, 06 2019. [Online]. Available: https://doi.org/10.1121/2.0001012

[33] D. Singh and M. Valdenegro-Toro, “The marine debris dataset for forward-looking sonar semantic segmentation,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops*, October 2021, pp. 3741–3749.

[34] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017.

[35] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” 2018. [Online]. Available: https://arxiv.org/abs/1804.02767

[36] L. Ge, P. Singh, and A. Sadhu, “Advanced deep learning framework for underwater object detection with multibeam forward-looking sonar,” *Structural Health Monitoring*, p. 14759217241235637, 2024.

[37] J. Helminen, “ARIS dataset: Three fish species,” 8 2021. [Online]. Available: https://figshare.com/articles/dataset/ARIS_dataset_Three_fish_species/14423630

[38] K. Xie, J. Yang, and K. Qiu, “A dataset with multibeam forward-looking sonar for underwater object detection,” *Scientific Data*, vol. 9, no. 1, Dec. 2022. [Online]. Available: http://dx.doi.org/10.1038/s41597-022-01854-w

[39] P. Skalski, “Make Sense,” https://github.com/SkalskiP/make-sense/, 2019.