

Acoustic 3D reconstruction of underwater infrastructure – possibilities, problems & potentials

David Brandt

*Institute for the Protection of Maritime Infrastructures
German Aerospace Center (DLR)
Bremerhaven, Germany
david.brandt@dlr.de*

Benjamin Lehmann

*Institute of Water-Acoustics, Sonar-Engineering and
Signal-Theory (IWSS), City University of Applied Sciences
Bremen
Bremen, Germany
benjamin.lehmann@hs-bremen.de*

Abstract— This work presents a review of the state of the art in generating three-dimensional models of underwater scenes with acoustic sensors. For each of the sensor types multibeam echosounder, forward looking multibeam, sidescan sonar (conventional and synthetic aperture), the physical properties of the sensor are investigated, specifically with regards to acoustic range, range resolution and angular resolution. Secondly, for each sensor a review is provided on the past and current strategies to generate or enhance three-dimensional information from the sensor data. The limitations of these methods are analyzed and future research fields are identified to maximize the potential derived from the physical sensor properties.

Keywords—sonar, 3D reconstruction, data fusion

I. INTRODUCTION

The mapping of the ocean floors and the survey of underwater infrastructure have always been important topics in the maritime world. With the recent rise in geopolitical tensions as well as the events in the Baltic Sea related to subsea pipelines and cables in particular, the critical need to ensure the safety and security of underwater infrastructure has increased significantly. Current methods struggle to provide reliable and efficient means to understand complex three-dimensional underwater scenes. Due to the inaccessibility and generally lower visibility underwater the data products required for comprehensive situational awareness can be difficult to acquire.

For detecting and identifying objects on a flat sea floor, two-dimensional sonar images are an established solution. In environments with vertical features like harbors or offshore energy installations, three-dimensional models are essential to capture all information needed for a comprehensive understanding of the scene. These models have to be detailed and accurate to permit identification of objects, risk analysis or structural fault assessment and allow safe underwater navigation.

This work aims at providing an overview about existing acoustic sensor types and methods which can be used to obtain high-resolution 3D models of underwater scenes. From the sensor's hardware constraints and the existing methods, a potential for further research is derived and further investigation into sensor data fusion between multibeam echosounder (MBES) and sidescan sonar (SSS) is suggested. To our knowledge this is the only dedicated review paper on dense underwater 3D reconstruction from acoustic sensors.

The main contributions from this work are

- A brief description of the working principle of four acoustic underwater sensors MBES, forward looking sonar (FLS), SSS and synthetic aperture sonar (SAS) including typical resolutions of commercially available systems (Section II)

- A comprehensive review on methods for dense 3D reconstruction from FLS, SSS and SAS data (Section III)
- A discussion on potential research fields based on the hardware constraints and the results of the existing reconstruction methods (Section IV)

Optical technologies like photogrammetry and lidar are not considered in this paper. They can, under the right circumstances, produce very detailed models [1] featuring color information. However, even though efforts are being made to increase performance in poor water conditions [2], these techniques cannot be relied upon in most regions where critical infrastructure is located. These regions tend to be busy, shallow and close to rivers which are all indicators of low visibility. For applications with good visibility, [2] gives a good overview on 3D reconstruction methods based on optical images. In addition, the authors mention a few selected acoustical methods, including less frequently used sensor types such as single beam sonars or mechanical scanning sonars, which are not discussed in this work, and expand on optical-acoustic fusion techniques.

II. HARDWARE OVERVIEW

A variety of acoustic sensors are employed for underwater mapping and object reconstruction, each offering distinct capabilities and limitations with respect to spatial resolution, coverage, and dimensionality. The following section provides an overview of the most commonly used systems—MBES, FLS, SSS, and SAS—highlighting their key characteristics and implications for three-dimensional reconstruction tasks. In Fig. 1, the working principles of these four sensors are illustrated. While MBES typically acquires data by looking downward at the scene, FLS, SSS, and SAS observe the scene from the side. All sensors can, depending on the setup, provide high range resolutions below 1 cm, which in Fig. 1 corresponds to the direction along the sonar beams, depicted as light-blue cones extending outward from the red sensor elements.

Multibeam echosounders (MBES) are established sensors for mapping the sea floor and in contrast to the other acoustic sensors discussed here directly delivers three-dimensional data. While their range resolution is below 1 cm for high-frequency systems, the horizontal resolution is limited because it linearly decreases with the distance from the sensor to the ensonified region. Minimum values for beamwidth are $0.5 - 2^\circ$ which result in footprints of 9 – 35 cm at nadir and 14 – 50 cm at a 45° incidence angle for a distance of 10 m to the insonified region. The MBES technology is generally set up so that it can deliver point clouds as a data product. 3D surface reconstruction from these point clouds is based on traditional algorithms like Poisson surface reconstruction, 2D

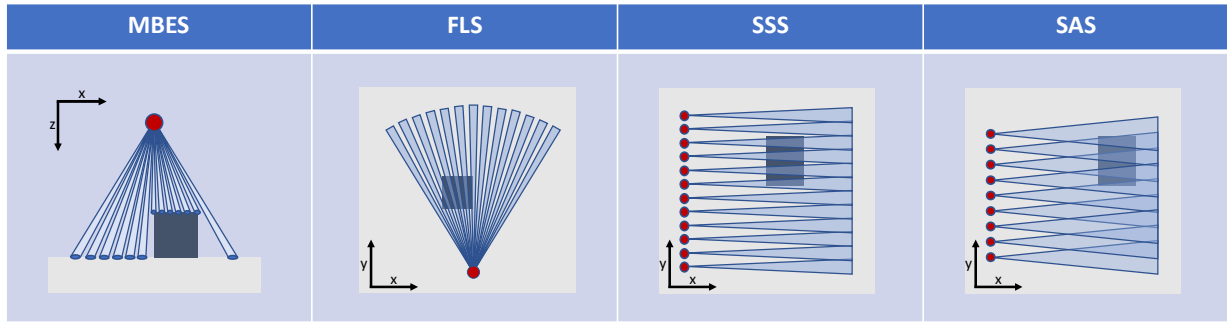


Fig. 1 Working principle of different sonar devices (red) imaging an object (dark) on the sea floor (light grey). High range resolutions in direction of the fan-shaped beams (light blue) are common to all systems. For MBES, FLS and SSS resolutions perpendicular to range depend on the beamwidth, for SAS this limitation is overcome by use of overlapping beams. MBES data can be interpreted as a set of 3D points (blue). FLS, SSS and SAS images are 2D projections of the scene.

Delaunay triangulation or the ball pivot algorithm [3–6]. Newer techniques have not been explored. Reasons for this may be the lack of high-resolution datasets which comes from the high cost associated with bringing the relatively bulky sensor very close to an object of interest. The smallest devices on the market measure 15 – 20 cm in all dimensions due to the perpendicular transmitter and receiver arrays.

Forward looking multibeam sonars (FLS) tend to be smaller (e.g. 12 cm × 12 cm × 6 cm) and can produce images with resolutions of down to 2 mm in range and 0.4° in horizontal beam width, which corresponds to 7 cm at a range of 10 m, by utilizing frequencies up to 3 MHz and bandwidths up to 375 kHz. The high attenuation of such short frequencies leads to limited ranges, making these sonars more suited for navigation and detailed inspection than mapping. Vertically, these systems typically use beam widths of around 20°.

With their high horizontal resolution and area coverage rate (30 m to 100 m to each side for high-frequency systems), sidescan sonars are an established tool for locating and identifying objects on the sea floor, but intrinsically provide only two-dimensional information. Range resolution is only a function of bandwidth (or pulse length), not distance, and can be as low as 0.6 cm. Along-track resolution decreases linearly with range. High-frequency systems reach resolutions of 3.5 cm at a range of 10 m. With additional hardware, bathymetric information can be collected using interferometry, but this technology is physically limited to slowly changing terrain and cannot be used for larger vertical structures [7].

Synthetic aperture sonar (SAS) systems are relatively costly and large in size (array lengths > 0.5 m) but allow for highly efficient area coverage (e.g. 200 m to 300 m to each side) at horizontal resolutions between 2 cm × 2 cm and 5 cm × 5 cm independent from range. As with sidescan sonar, interferometry can be used to acquire bathymetric data, but similar restrictions apply. Even though recent efforts show potential for improving performance [8, 9], vertical uncertainties remain at least one order of magnitude higher than for multibeam echosounder systems. Additionally, the horizontal resolution for 2D imaging is not retained for the interferometric data.

III. 3D RECONSTRUCTION METHODS

Since FLS, SSS and SAS do not intrinsically provide 3D information as the MBES does, there have been several different approaches for each sensor to reconstruct this information from the 2D images or raw data. They can roughly

be clustered into voxel-based methods, methods based on the shape from shading technique and methods using neural networks, with Gaussian splatting and circular SAS standing out from the rest. For each of these an overview of the methods, the applications and the results is given, also highlighting some of the limitations. This review is limited to techniques for dense reconstruction where the shape of reconstructed objects can be visually inferred from the model without prior knowledge. Methods only providing sparse information for underwater navigation are not included.

A. Voxel-based methods

Most methods for reconstruction of 3D data from FLS images are based on some generalized form of space carving [10]. The area of interest is modeled as a 3D grid composed of so-called voxels, the 3D equivalent of pixels. In traditional space carving, the voxels are initially considered occupied. For each image, it is calculated which voxels contribute to which image pixel. Based on the image information for each pixel, the probability of occupancy is adjusted for the corresponding voxels. The more images from different viewpoints are considered, the more is carved away from the model until only the actual scene remains. These methods rely on images from multiple views which makes the technique particularly suited for FLS which captures a full 2D image for every ping, in contrast to SSS and SAS, where one image is always composed of many successive pings. Therefore, except for [11] the methods described in this subsection are all developed for FLS data. They are tailored towards reconstruction of isolated objects with dimensions between 10 cm and 1 m which can be investigated with a FLS from all sides and from different elevation angles. Typically, the sensor is brought very close to the object, leading to images with resolutions of few millimeters and models with resolutions of few centimeters. The sea floor is, for most investigations using this technique, not considered as part of the scene and the corresponding voxels are considered unoccupied.

The space carving technique is applied to a variety of objects in [12] and [13]. On the FLS image, the leading edge of an object is detected, and all voxels inside the beam leading up to that edge are classified as empty. In this way, a volume discretized with voxels presumed filled at the start is “carved out” by multiple views from different directions. The authors show that the reconstruction result is highly dependent on the choice of viewing angles.

In another approach, 2.5D elevation maps are formed by segmentation and classification of the FLS image in object, shadow and background regions [12]. Object and shadow regions on a 2D grid based on a flat sea floor are assumed occupied, background regions unoccupied. The elevation of the occupied regions is determined by measuring the shadows and again assuming a flat sea floor.

The method in [13] initializes the probability of a voxel being occupied to 0.5 and updates it with every FLS image based on probabilities from very basic pixel-wise classification in object and noise based on intensity histograms. The combination of two orthogonally mounted sonars is explored. A 2D occupancy map is built from FLS data in [14], where intensities above a certain threshold indicate occupied grid elements, intensities below a second threshold (shadows) are considered unknown and all others are marked as empty. The method is supported by a singlebeam profiling sonar. All grid elements up to a detected object are considered empty, the element at the detection point is marked as occupied, and all elements behind are labeled as unknown.

An approach similar to space carving is described in [15] and [16] where each voxel is assigned the lowest observed intensity of multiple views.

In [11] a voxel-based approach for SSS data is proposed, optimizing grid occupancy through a graph representation of occupied voxels. Simulative results reconstructing the general shape of a slightly sloped sea floor are presented in [17, pp. 269-280], comparing different voxel initializations qualitatively. In addition to classical space carving, variations with an initially unoccupied volume and an initialization plane are explored.

B. Shape from shading

The idea to apply the shape from shading technique, which was initially developed for the 3D reconstruction from monocular optical images [18], on sonar images, was introduced in 1991 [19, 20].

The basic principle is an optimization including the following steps:

- model a 3D environment
- simulate sonar data from that model
- compare simulated data to real data
- adjust model

With shape from shading for SSS or SAS, swath widths of several hundred meters can be reconstructed at once. Theoretically, the technique allows to take full advantage of the sensor resolution, although mostly it is still scaled down to allow for faster computation times. Most approaches only reconstruct a height map with exactly one elevation value corresponding to each coordinate in the horizontal plane. This does not allow vertical surfaces or even overhanging structures to be reconstructed. Generally, the technique is able to reconstruct the gradients of a 3D environment with relatively high accuracy, but absolute height estimates are less accurate since in the existing variations of the technique, only very sparse control points from other data sources are used, if any.

Very sparse multibeam echosounder data with point spacing of several hundred meters is used in [20] to initialize the modeling of a seamount with SSS data, progressively increasing resolution to 50 m × 50 m.

The approach introduced in [19] is expanded upon in [21], where both synthetic and real results from mapping a deep-sea ridge are presented. The method includes both local and global optimization steps that are iteratively applied.

An approach using step-wise resolution enhancement similar to the concept in [20] is described in [22]. The method is evaluated qualitatively on real data of relatively flat sea floor with ripples, rocks and a pipeline as well as augmented objects. Assuming a perfectly straight sensor trajectory, the model accommodates the full resolution of the SSS data which is 3 cm to 12 cm in this case. The radius of the pipeline is estimated at (0.51 ± 0.19) m, compared to a ground truth of 0.38 m.

An approach similar to shape from shading techniques is presented in [23]. It estimates elevations one ping at a time, considering the shadow lengths cast by objects on the sea floor. This method is extended in [24] to incorporate information from one prior ping, and further applied to SAS data in [25]. More detailed discussions and visual examples, such as reconstructions of a tire and a shipwreck section, are found in [26], though the results are not evaluated quantitatively.

Reference [27] introduces a shape from shading approach based on the Lambertian scattering model from [22], using a multilayer perceptron (MLP) to encode 3D information. The method enables fusion of data from multiple SSS tracks, but resolution is constrained by the MLP size, requiring downsampling to 64 data points per ping. As a result, only larger rocks are reconstructed, and accuracy varies between sparse altimeter control points.

Shape from shading is also performed on SSS images in [28], where images are first decomposed into low- and high-frequency components. This step improves the signal-to-noise ratio in a dataset containing a shipwreck and different sea floor types.

In contrast to all the previously discussed approaches, [29] shows, that shape from shading for sonar data can be deployed for modeling truly three-dimensional structures including vertical surfaces. A local shape from shading method is used to fill in the geometry of pillars whose edges have been previously detected and localized. A voxel-based approach is employed to fuse the data from multiple frames. While simple structures with approximate dimensions of 0.7 m × 2.0 m are reconstructed using 10 cm voxel sizes, the output is limited to small patches of the structure surfaces.

A similar method for FLS data is presented in [30], where the shape from shading technique is applied locally to reconstruct simple objects placed on a flat sea floor. As in [29], segmentation and classification of the FLS image are used to define object boundaries prior to reconstruction.

C. Neural Networks and Gaussian splatting

For both small-scale objects imaged with forward-looking sonar (FLS) and large-scale areas surveyed with sidescan sonar (SSS), data-driven methods employing neural networks have demonstrated the potential to reconstruct three-dimensional information from two-dimensional sonar imagery. Although these approaches are, in principle, capable of achieving arbitrarily high spatial resolutions, current neural network architectures typically require substantial downscaling of the input data, particularly for extensive

survey regions. The reconstruction quality is highly dependent on the characteristics of the training data.

An additional promising technique originating from the optical domain is Gaussian splatting. While this method has not yet been applied exclusively to acoustic underwater data, preliminary studies in [31] indicate its adaptability for use with FLS.

A convolutional neural network (CNN) is trained in [32] to predict elevation angles for each pixel in a FLS image, enabling 3D reconstruction from single or very few images. For training, the simulator introduced in [22] is used.

Building on this concept, [33] proposes training a CNN to generate front-view depth maps from FLS images. These maps correspond to the view an RGB-D camera would capture if placed at the same location as the FLS sensor. Training data are generated by modeling scenes in Blender, and a CycleGAN is used to transform the rendered images to resemble real sonar data. Both approaches are evaluated on simple geometric shapes ranging from 8 cm to 30 cm in size, placed either on the sea floor or suspended in the water column. Quantitative evaluations are provided. The models exploit the high resolution of a 3 MHz FLS with an artificially limited viewing range of 1.5 m, achieving resolutions of 3 mm in range and 1 cm to 3 cm in the other two spatial dimensions.

In [34], two CNNs for image-to-image translation are trained using MBES and SSS data to predict height profiles from SSS imagery alone. The method reconstructs rocks of various sizes but is constrained by the resolution of the MBES training data and by the downscaling of input images to (265×265) pixels. Reconstruction accuracy is further improved in [35] by incorporating sparse bathymetric data. In [36], it is demonstrated that overlapping SSS tracks can be fused into a single 3D model, yielding better results than reconstruction from a single pass alone. The network is extended in [37] by integrating an MLP, similar to the one used in [27], to predict environmental gradients. This model combines sidescan images, sparse bathymetry, and the output of the CNN from [34]. Treating the SSS data as images of (64×512) pixels allows for a twofold increase in resolution. For a swath width of 100 m, this corresponds to approximately 20 cm per pixel in the across-track direction which is still significantly coarser than the resolution of the original SSS data. Furthermore, the method remains inherently limited by the resolution of the MBES data used for training.

In [28], a monocular depth estimation network is trained on optical data and applied to SSS data. The results exhibit substantial faults which fail to be corrected by combining the results with those of a shape from shading approach.

Reference [31] shows that Gaussian splatting, a 3D reconstruction technique from the optical domain [38] that has gained very strong traction recently, can be adapted for use with FLS images. After fusion with optical data, an object with dimensions between few centimeters and few decimeters is reconstructed as a point cloud with high resolution but with a lot of noise. The use of sonar data only is not investigated. Gaussian splatting stores information about the scene as a collection of 3D gaussians with different properties. Images can then be rendered very efficiently by simple transformations called splatting.

D. Circular SAS

Circular SAS is a technique where a target is captured from all sides by moving the sensor in a circle around the target [39–43]. With a three-dimensional trajectory like a spiral or multiple circles with different heights, this technique can be used for 3D modelling with very fine detail. In contrast to the algorithms discussed above, the 3D model is not reconstructed from 2D images but from raw sonar data.

In [44] it is shown, that the vertical beamforming from interferometric SAS processing can, after multiple alignment steps, be used to reconstruct 3D objects from multiple circular scans in different heights or with different radii. Results are shown where munitions, an oil barrel and an aluminum cylinder with dimensions between 15 cm and 90 cm are reconstructed with such high detail in some cases that a rope and some material boundaries of dimensions around 1 cm are discernable.

In [45] a neural rendering framework similar to neural radiance fields (NeRF) from the optical domain [46] is introduced and compared to classical SAS processing using coherent backpropagation. Both approaches are used to reconstruct complex figurines with total dimensions of about 20 cm and features with sizes below 1 cm with a circular SAS in air in a laboratory environment. Additionally, a cinder block and a cylinder with estimated dimensions between 25 cm and 100 cm and features with sizes of few centimeters are reconstructed using a bistatic Sediment Volume Search Sonar with frequencies around 30 kHz.

IV. SUGGESTED RESEARCH FIELDS

As outlined in Section II, MBES exhibit physical and functional characteristics that complement those of the other commonly used acoustic sensors. MBES provide high-resolution measurements in the vertical direction and deliver reliable three-dimensional point clouds. In contrast, the sensor types FLS, SSS and SAS acquire high-resolution data laterally and produce two-dimensional images that lack intrinsic depth information. While gradients in the third dimension can be inferred from these 2D imaging sensors, reconstructed depths exhibit high uncertainties. Given these complementary strengths and weaknesses, there is strong motivation to pursue further research into acoustic sensor data fusion methods. Combining the precise and explicitly three-dimensional depth measurements of MBES with the high-resolution lateral imaging capabilities of FLS, SSS, or SAS may lead to more robust and detailed 3D reconstructions of underwater environments.

FLS, when combined with volumetric reconstruction techniques such as space carving, and SAS in circular SAS configurations, are particularly suited for the reconstruction of isolated objects that can be imaged from multiple directions. Typical targets are of sizes between 10 cm and 1 m and can be reconstructed well enough to discern features as small as 1 cm. In scenarios involving such small, isolated targets that are accessible from all sides, it becomes unclear in which cases MBES can be deployed sufficiently close to contribute meaningful additional data but not so close that it could perform the reconstruction alone. Conversely, SSS is highly effective for surveying larger or more complex structures, offering area coverage rates that exceed, but remain comparable to, those of MBES. Additionally, SSS-based reconstructions, whether using shape from shading techniques or data-driven approaches such as neural networks, typically

operate with one or a limited number of passes and do not necessarily require views from all sides.

In conclusion, the complementarity in spatial resolution and the comparable survey characteristics motivate further investigation into the fusion of SSS and MBES data to leverage the strengths of both systems for enhanced 3D reconstruction of underwater infrastructure. Currently available reconstruction algorithms for SSS are mostly based on the shape from shading technique. It has been shown in literature that this method can benefit from sparse 3D data from other sensors, but an integration with dense MBES data as from a survey of special or exclusive order according to IHO Standard S-44 [47] which corresponds to resolutions of 10 cm to 20 cm [48] has yet to be investigated.

V. REFERENCES

- [1] Magellan, "Magellan Titanic – TT24," *Magellan*, Jun. 17, 2024. [Online]. Available: <https://www.magellan.gg/magellan-titanic-tt24> [accessed: Feb. 23 2025].
- [2] K. Hu *et al.*, "Overview of Underwater 3D Reconstruction Technology Based on Optical Images," *Journal of Marine Science and Engineering*, vol. 11, no. 5, 2023, doi: 10.3390/jmse11050949.
- [3] R. Campos, R. Garcia, P. Alliez, and M. Yvinec, "A surface reconstruction method for in-detail underwater 3D optical mapping," *The International Journal of Robotics Research*, vol. 34, no. 1, pp. 64–89, 2015, doi: 10.1177/0278364914544531.
- [4] R. Campos, R. Garcia, and T. Nicosevici, "Surface reconstruction methods for the recovery of 3D models from underwater interest areas," in Proc. OCEANS 2011 IEEE - Spain, 2011, pp. 1–10, doi: 10.1109/Oceans-Spain.2011.6003633.
- [5] M. Kulawiak and Z. Łubniewski, "3D Object Shape Reconstruction from Underwater Multibeam Data and Over Ground Lidar Scanning," *Polish Maritime Research*, vol. 25, no. 2, pp. 47–56, 2018, doi: 10.2478/pomr-2018-0053.
- [6] D. Lu, H. Li, Y. Wei, and T. Shen, "An improved merging algorithm for delaunay meshing on 3D visualization multibeam bathymetric data," in Proc. The 2010 IEEE International Conference on Information and Automation, 2010, pp. 1171–1176, doi: 10.1109/ICINFA.2010.5512309.
- [7] V. B. Pimentel, C. Florentino, and A. A. Neto, "Evaluation of the precision of phase-measuring bathymetric side scan sonar relative to multibeam echosounders," *International Hydrographic Review*, Nov., no. 24, pp. 61–84, 2020.
- [8] S. Steele and R. Charron, "Interferometric synthetic aperture sonar bathymetry maps using ensembles," in Proc. Synthetic Aperture Sonar and Synthetic Aperture Radar 2023, 2023, doi: 10.25144/15943.
- [9] O. J. Lorentzen, T. O. Saebo, and R. E. Hansen, "Backscatter Features for Estimating Synthetic Aperture Sonar Bathymetry," in Proc. Global Oceans 2020: Singapore – U.S. Gulf Coast, 2020, pp. 1–4, doi: 10.1109/IEEECONF38699.2020.9389076.
- [10] K. N. Kutulakos and S. M. Seitz, "A Theory of Shape by Space Carving," *International Journal of Computer Vision*, vol. 38, no. 3, pp. 199–218, 2000, doi: 10.1023/A:1008191222954.
- [11] A. P. Philipp Woock, "Bayesian reconstruction of seafloor shape from side-scan sonar measurements using a Markov random field," in Proc. International Conference and Exhibition on Underwater Acoustics (UA) 2014, 2014, pp. 1563–1570.
- [12] W. Xu, J. Yang, H. Wei, H. Lu, X. Tian, and X. Li, "Seabed mapping for deep-sea mining vehicles based on forward-looking sonar," *Ocean Engineering*, vol. 299, 2024, doi: 10.1016/j.oceaneng.2024.117276.
- [13] D. P. Horner, N. McChesney, T. Masek, and S. P. Kragelund, "3D reconstruction with an AUV mounted forward looking sonar," in Proc. International Symposium on Unmanned Untethered Submersible Technology, 2009, pp. 1464–1470.
- [14] E. Hernández, P. Ridao, A. Mallios, and M. Carreras, "Occupancy Grid Mapping in an Underwater Structured Environment," in Proc. 8th IFAC International Conference on Manoeuvring and Control of Marine Craft, 2009, pp. 286–291, doi: 10.3182/20090916-3-BR-3001.0049.
- [15] T. Guerneve and Y. Petillot, "Underwater 3D reconstruction using BlueView imaging sonar," in Proc. Oceans 2015 - Genova, 2015, pp. 1–7, doi: 10.1109/OCEANS-Genova.2015.7271575.
- [16] 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, doi: 10.1002/rob.21783.
- [17] P. Woock, "Umgebungskartenschätzung aus Sidescan-Sonardaten für ein autonomes Unterwasserfahrzeug," Ph.D. dissertation, Karlsruher Institut für Technologie (KIT), Karlsruhe, 2015.
- [18] B. K. Horn, "Shape from Shading: A Method for Obtaining the Shape of a Smooth Opaque Object from One View," Ph.D. dissertation, Massachusetts Institute of Technology, Cambridge, MA, 1970.
- [19] D. Langer and M. Hebert, "Building qualitative elevation maps from side scan sonar data for autonomous underwater navigation," in Proc. 1991 IEEE International Conference on Robotics and Automation, 1991, pp. 2478–2483, doi: 10.1109/ROBOT.1991.131997.
- [20] R. Li and S. Pai, "Improvement Of Bathymetric Data Bases By Shape From Shading Technique Using Side-scan Sonar Images," in Proc. OCEANS 91, 1991, pp. 320–324, doi: 10.1109/OCEANS.1991.613950.
- [21] A. E. Johnson and M. Hebert, "Seafloor map generation for autonomous underwater vehicle navigation," *Autonomous Robots*, vol. 3, pp. 145–168, 1996, doi: 10.1007/BF00141152.
- [22] E. Coiras, Y. Petillot, and D. M. Lane, "Multiresolution 3-D reconstruction from side-scan sonar images," *IEEE transactions on image processing*, vol. 16, no. 2, pp. 382–390, 2007, doi: 10.1109/tip.2006.888337.
- [23] K. Bikonis, Z. Lubniewski, M. Moszynski, and A. Stepnowski, "Three-dimensional imaging of submerged objects by sidescan sonar data processing," in Proc. 1st International Conference on Underwater Acoustic Measurements, 2005.

- [24] Z. Lubniewski and K. Bikonis, "Seafloor relief reconstruction from side scan sonar data," *Hydroacoustics*, vol. 10, 2007.
- [25] K. Bikonis, A. Stepnowski, and M. Moszynski, "Computer Vision Techniques Applied for Reconstruction of Seafloor 3D Images from Side Scan and Synthetic Aperture Sonars Data," *The Journal of the Acoustical Society of America*, vol. 123, no. 5, 2008, doi: 10.1121/1.2935303.
- [26] K. Bikonis, M. Moszynski, and Z. Lubniewski, "Application of Shape From Shading Technique for Side Scan Sonar Images," *Polish Maritime Research*, vol. 20, no. 3, pp. 39–44, 2013, doi: 10.2478/pomr-2013-0033.
- [27] N. Bore and J. Folkesson, "Neural Shape-From-Shading for Survey-Scale Self-Consistent Bathymetry From Sidescan," *IEEE Journal of Oceanic Engineering*, vol. 48, no. 2, pp. 416–430, 2023, doi: 10.1109/JOE.2022.3215822.
- [28] Y. Ju *et al.*, "Three-dimensional reconstruction of underwater side-scan sonar images based on shape-from-shading and monocular depth fusion," *Intelligent Marine Technology and Systems*, vol. 2, no. 1, 2024, doi: 10.1007/s44295-023-00013-0.
- [29] E. Westman and M. Kaess, "Wide Aperture Imaging Sonar Reconstruction using Generative Models," in *Proc. 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019, pp. 8067–8074, doi: 10.1109/IROS40897.2019.8967934.
- [30] M. D. Aykin and S. Negahdaripour, "Forward-look 2-D sonar image formation and 3-D reconstruction," in *Proc. 2013 OCEANS - San Diego*, 2013, pp. 1–10, doi: 10.23919/OCEANS.2013.6741270.
- [31] Z. Qu *et al.*, "Z-Splat: Z-Axis Gaussian Splatting for Camera-Sonar Fusion," *IEEE transactions on pattern analysis and machine intelligence*, 2024, doi: 10.1109/TPAMI.2024.3462290.
- [32] R. DeBortoli, F. Li, and G. A. Hollinger, "ElevateNet: A Convolutional Neural Network for Estimating the Missing Dimension in 2D Underwater Sonar Images," in *Proc. 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019, pp. 8040–8047, doi: 10.1109/IROS40897.2019.8968121.
- [33] Y. Wang, Y. Ji, D. Liu, H. Tsuchiya, A. Yamashita, and H. Asama, "Elevation Angle Estimation in 2D Acoustic Images Using Pseudo Front View," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 1535–1542, 2021, doi: 10.1109/LRA.2021.3058911.
- [34] Y. Xie, N. Bore, and J. Folkesson, "Inferring depth contours from sidescan sonar using convolutional neural nets," *IET Radar, Sonar & Navigation*, vol. 14, no. 2, pp. 328–334, 2020, doi: 10.1049/iet-rsn.2019.0428.
- [35] Y. Xie, N. Bore, and J. Folkesson, "High-Resolution Bathymetric Reconstruction From Sidescan Sonar With Deep Neural Networks," *arxiv.org*, Jun. 2022. [Online]. Available: <http://arxiv.org/pdf/2206.07810v1>.
- [36] Y. Xie, N. Bore, and J. Folkesson, "Bathymetric Reconstruction From Sidescan Sonar With Deep Neural Networks," *IEEE Journal of Oceanic Engineering*, vol. 48, no. 2, pp. 372–383, 2023, doi: 10.1109/JOE.2022.3220330.
- [37] Y. Xie, N. Bore, and J. Folkesson, "Neural Network Normal Estimation and Bathymetry Reconstruction From Sidescan Sonar," *IEEE Journal of Oceanic Engineering*, vol. 48, no. 1, pp. 218–232, 2023, doi: 10.1109/JOE.2022.3194899.
- [38] B. Kerbl, G. Kopanas, T. Leimkuehler, and G. Drettakis, "3D Gaussian Splatting for Real-Time Radiance Field Rendering," *ACM Transactions on Graphics*, vol. 42, no. 4, pp. 1–14, 2023, doi: 10.1145/3592433.
- [39] T. M. Marston, J. L. Kennedy, and P. L. Marston, "Coherent and semi-coherent processing of limited-aperture circular synthetic aperture (CSAS) data," in *Proc. OCEANS'11 MTS/IEEE KONA*, 2011, pp. 1–6, doi: 10.23919/OCEANS.2011.6107280.
- [40] Y. Pailhas, Y. Petillot, and B. Mulgrew, "Increasing circular synthetic aperture sonar resolution via adapted wave atoms deconvolution," *The Journal of the Acoustical Society of America*, vol. 141, no. 4, pp. 2623–2632, 2017, doi: 10.1121/1.4979807.
- [41] J. D. Park, T. E. Blanford, D. C. Brown, and D. Plotnick, "Alternative representations and object classification of circular synthetic aperture in-air acoustic data," *The Journal of the Acoustical Society of America*, vol. 148, no. 4, p. 2661, 2020, doi: 10.1121/1.5147416.
- [42] A. Reed, T. Blanford, D. C. Brown, and S. Jayasuriya, "SINR: Deconvolving Circular SAS Images Using Implicit Neural Representations," *IEEE Journal of Selected Topics in Signal Processing*, vol. 17, no. 2, pp. 458–472, 2023, doi: 10.1109/JSTSP.2022.3215849.
- [43] A. D. Friedman, S. K. Mitchell, T. L. Kooij, and K. N. Scarbrough, "Circular synthetic aperture sonar design," in *Proc. Europe Oceans 2005*, 2005, 1038–1045 Vol. 2, doi: 10.1109/OCEANSE.2005.1513201.
- [44] T. M. Marston and J. L. Kennedy, "Volumetric Acoustic Imaging via Circular Multipass Aperture Synthesis," *IEEE Journal of Oceanic Engineering*, vol. 41, no. 4, pp. 852–867, 2016, doi: 10.1109/JOE.2015.2502664.
- [45] A. Reed, J. Kim, T. Blanford, A. Pediredla, D. Brown, and S. Jayasuriya, "Neural Volumetric Reconstruction for Coherent Synthetic Aperture Sonar," *ACM Transactions on Graphics*, vol. 42, no. 4, pp. 1–20, 2023, doi: 10.1145/3592141.
- [46] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng, "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis," *Communications of the ACM*, vol. 65, no. 1, pp. 99–106, 2022, doi: 10.1145/3503250.
- [47] International Hydrographic Organization (IHO), "S-44," S-44, Monaco, Oct. 2024.
- [48] International Hydrographic Organization (IHO), "Seafloor classification and Feature Detection: Chapter 4," in *Manual on Hydrography*, IHO Publication C-13, Monaco, 2011.