3D Data Products in the Marine Industry: A 2024 Review

2024 October 1

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Technological advancements in computing and analytics are taking knowledge-based industries into a new frontier. Three dimensional (3D) mapping and modeling have been advancing industries as a conduit for the application of many new technologies. The marine industry is part of this advancement, with it's own unique opportunities and challenges. This paper will take a closer look at the current research, industry parallels and expected developments in the application of 3D mapping and modeling in the marine industry.

3D Mapping

Ecological mapping of habitats and their complexity in marine environments is crucial to supporting conservation. As of 2019, only 5% of the marine ecological landscape was estimated to be satisfactorily mapped (Rossi & Orejas, 2019). Biodiversity mapping for marine animals requires a 3D approach due to the volumetric distribution of the animals, and this requirement is crucial to prevent underestimation. A purely 2D approach is susceptible to under-compensation, but a 2.5D (compilation of 2D scans in the z-axis) or a 3D approach also requires compensation for the temporal movement of the animals (Duffy & Chown, 2017).

High-resolution and detailed benthic maps are crucial to understand the available habitat for marine wildlife. A growing technique is the combination of LiDAR and photogrammetry to produce 3D maps of habitats, including biodiversity hotspots such as coral reefs, at the centimeter scale. The fine scale also requires that the measurement of equipment attitude is more precise to keep the margin of error for the LiDAR and photogrammetry data under acceptable levels. LiDAR generates a point-cloud, which is then processed to create a clean mesh on which photogrammtery data can be masked on to produce detailed surface texture and features. This data can then further be combined with Machine (ML) or Artificial Intelligence (AI) to classify organisms and habitat features. Semi-automatic and completely automatic methods are being demonstrated as a feasible means of substantially reducing human involvement in habitat classification (Mohamed et al., 2021)(Sauder et al., 2024). This approach of combining remote-sensing with ML is allowing the creation of valuable data and models that can allow conservation efforts to scale up. Figure 1 sketches the general workflow used to generate such habitat maps.

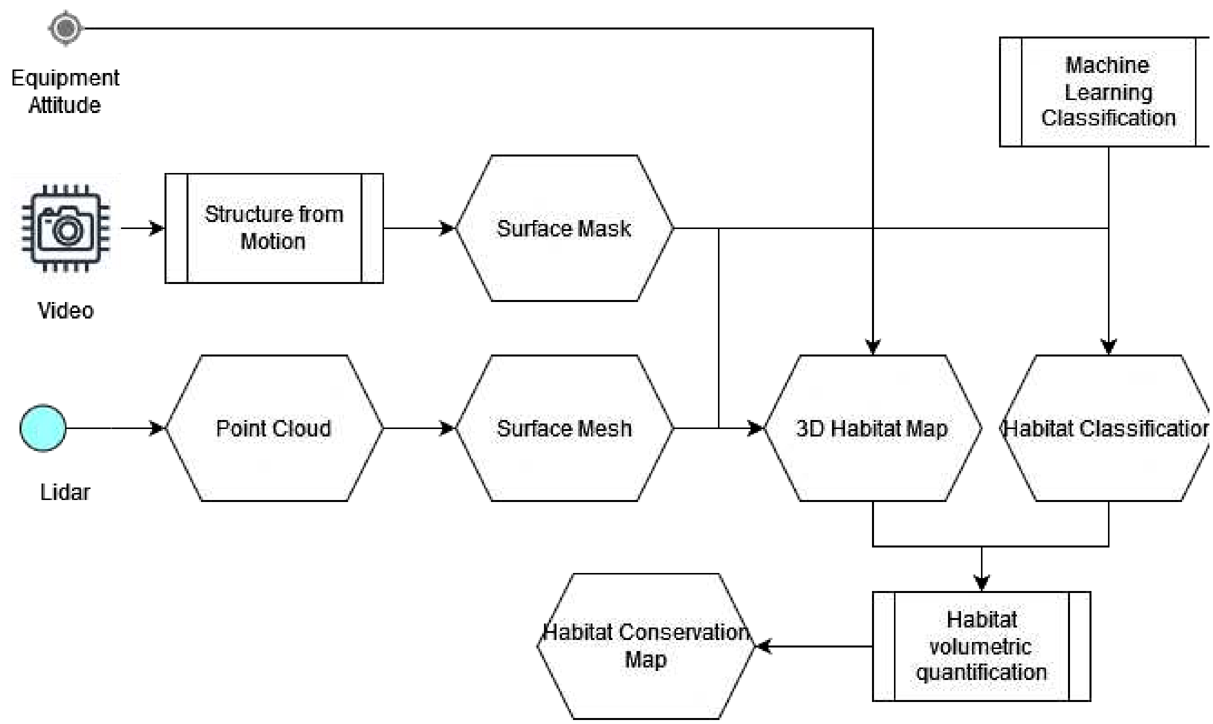

Figure 1: Generalized workflow for using semi- or fully- automatic classification of marine ecological habitat.

Another means of scanning and mapping of the ocean floor is acoustics, either as Echo Sounders or Sonar, are part of most ships today. As sound travels better in water than other means, they become the most common means for a vessel to inspect and observe below the water. Sonar can be create coarse resolution 3D models of the sea floor. The use of multi-beam sonars has been a common practice for ocean floor mapping at a resolution of ~10 km. Echo sounders are widely used on merchant ships but the data they collect is very low resolution for mapping.

Detailed mapping of the ocean floor also opens up avenues to study the geology for minerals. Josso et al., 2023, combined machine learning classification to generate an ocean floor probability map for the occurrence of Fe-Mn crusts. Increased resolution of multi-spectral photography, acoustic surveys and Photogrammetry has the potential to increase the efficiency geological surveys for minerals and geological landforms, though visual methods are harder to implement in deep marine environments when compared to acoustic methods (Joo et al, 2020)(Liu et al, 2020).

3D Modeling

Maritime operations rely on waterborne vessels, that require design, construction, inspections and maintenance. Inspections and maintenance are a routine task that are essential to safe and compliant operations. Structure damage and corrosion must be tracked, much like for civil infrastructure, so they can be addressed timely. The elimination of a human from the process is, for the foreseeable future, not practical, but the use of autonomous technologies and AI can greatly assist and streamline the process. Bonnin-Pascual & Ortiz, 2019, explored scientific literature on the pairing of autonomous data collection with AI assisted-classification to conduct inspections of vessels. They found that the technologies for this combined application can be deployed in the present and their applicability will become more reliable and detailed once they have been refined a bit further. 3D modeling plays a key role in providing data for human supervision, especially when insights need to be generated by analyzing depth or integration with technologies such as Augmented Reality (AR).

Future Growth

The expected trajectory of the evolution of 3D mapping and modeling in marine environments can draw many parallels to their terrestrial counterparts. Autonomous Underwater Vehicles (AUV) and Remote Operated Vehicles (ROV) are expected to become more widely deployed in marine environments. Not only have research studies and preliminary industry applications benefited greatly from their adoption, but their continued application will only refine the technology and improve the value in using them. Hence, their role in 3D mapping can be expected to gradually increase. However, the equipment has a large cost to it when compared to the existing methods used, and when accounting for the large volumetric scale of marine environments, traditional methods, which include things like cameras being dragged behind manned boats or those equipped by human divers, should remain in use for the foreseeable future. A gap that does and will continue to exist is; data. More intelligent systems will require more data, while the field is already lacking. Hence, AUVs and ROVs will always have a strong use case where large amounts of data are needed, especially for the creation and use of more advanced modeling.

Another parallel to draw, is the increasing use of machine learning and deep learning models, that are becoming more complex and capable. These models, which can be developed to autonomously categorize data on designated patterns, can take over a large amount of human work load when it comes to transforming raw data. Their use will only grow in the coming years and we expect that this will greatly increase the productivity of marine mapping initiatives. The gaps in data analytics, specifically identified by Rossi et al., 2019, will be filled initially through manual effort, that will be needed to train these algorithms. The semi-autonomous approach by Mohamed et al, 2021 and fully-autonomous approached by Sauder et al., 2024, are examples of what this approach will look like. As the accuracy and integration of these models increases, so will the scale of their application. Since the methods are currently excelling in academic testing for marine conservation, this field can be expected to be the first to benefit from this approach. However, due to the economic incentives behind geological surveys, that field should also be expected to soon develop its own models and technological integration. Hence, we can expect that 3D mapping will continue to provide a bridge between future conservation and survey efforts, especially through integration with AUVs and ROVs data collection.

Such 3D mapping endeavors, however, are resource intensive. They are not currently suitable for real-time or quick data analytics, which takes away from one of the potential use cases of deploying ROVs and AUVs for data collection or monitoring. LiDAR especially, can be very extensive and data heavy, making it very challenging for interpretation for quick use. To address this, Papadopoulos et al., 2011, demonstrated how by using simplification algorithms, LiDAR point clouds can quickly be translated to coarse level maps for web deployment, while still reserving the high-resolution output for a later instance of analysis. Hence, we can see a strong use case for a platform that analyzes marine mapping data for a flexible use case, including automated identification through learning models and near-real time web-available maps. We can expect their existing spatial analytics software to evolve by integrating such capabilities, or a new platform that caters to AUV and ROV data collection, as discussed before.

We must also make a special mention of citizen science. Manual efforts by private citizens can be invaluable to filling in deficiencies when it comes to 3D mapping of marine habitats, especially for conservation. Many coastlines do, and will probably continue to, lack the resources to deploy intensive surveying technologies. In these areas, citizen scientists will be crucial in updating data as well as compensating the initial demand of manual verification, though public training will be required to ensure data quality (Rossi et al. 2019). Sauder et al., 2024, recently demonstrated a completely automatic classification method for coral reef monitoring, by pairing deep-learning AI with video footage collected by human divers. This method also holds potential to use footage collected by local divers and utilize a learning model to provide classification and update data.

3D modeling will continue to develop, but its biggest bottleneck right now, is the integration of the different technologies that allow the workflow to come together. An increased use of ROVs and drones is expected, though the adoption rate will remain to be seen. An entire separate commentary can be made on the development of learning models for use in infrastructure and equipment inspections. Overall, a strong use case exists, especially financially. We can expect such technologies to roll out increasingly as the models become better and more integrated on existing platforms. There are also the technologies of Augmented Reality (AR) and Digital Twining. These are of particular interest as they will make the industry more dynamic, as well as utilize 3D modeling as a rudimentary form of data for their own operations. However, AR technologies are currently lagging in their practical application (Mascareñas et al. 2021) (Gernez et al., 2020). We speculate that once the hardware reaches an acceptable level of application for widespread commercial or military application, it would be ready for adoption in the maritime industry as well. Digital Twining is a technology that allows monitoring and analysis of 3D models, remotely. With advancement in the technology and the rise of more complex machine learning algorithms, the workflow of generating Digital Twins through 3D models is likely to become more widely used and automated (Lv et al., 2023). It is a technology who's use cases will continue to emerge as it grows.

The sharing and availability of data, especially privately collected data, is of great concern that the maritime industry must address (Jewkes, 2024). As with other industries, data is becoming increasingly valuable. This inherently creates little incentive to invest in making data openly available. Also, there is little common oversight or collaboration across the various stakeholders in the industry, resulting in different standards of data collection and segregated ownership. The solution to such inaccessibility, depends entirely on market forces, and can play out in many a ways. In the absence of regulation, government investment, and collaborative market forces, the collaboration of private entities for data sharing is likely to be limited, if not entirely absent from an industry. Government and regulatory forces can often either invest public money or dictate industry collaboration to address similar challenges. However, competing geopolitical interests, international laws, cross-border treaties and limiting jurisdictions, make this topic unique, as well as more challenging to address in this industry.

To conclude, we can see that the evolution and adaption of new technologies in the maritime industries is dynamic. It will rely on 3D mapping and modeling to enable these technologies. Investments in 3D mapping and modeling workflows and integration with service platforms will provide comprehensive growth for the industry. However, limitations from available resources and competing interests will dictate exactly how such investments will manifest. The industry will benefit from aligning itself to capitalize on these developments.

REFERENCES

Bonnin-Pascual, F., & Ortiz, A. (2019). On the use of robots and vision technologies for the inspection of vessels: A survey on recent advances. *Ocean Engineering*, *190*, 106420. https://doi.org/10.1016/j.oceaneng.2019.106420

Duffy, G. A., & Chown, S. L. (2017). Explicitly integrating a third dimension in marine species distribution modelling. *Marine Ecology Progress Series*, *564*, 1–8. https://doi.org/10.3354/meps12011

Florinsky, I. V., & Filippov, S. V. (2021). Three-Dimensional Geomorphometric Modeling of the Arctic Ocean Submarine Topography: A Low-Resolution Desktop Application. *IEEE Journal of Oceanic Engineering*, *46*(1), 88–101. IEEE Journal of Oceanic Engineering. https://doi.org/10.1109/JOE.2020.2969283

Gernez, E., Nordby, K., Eikenes, J. O., & Hareide, O. S. (2020). A review of augmented reality applications for ship bridges. *159-186*. https://fhs.brage.unit.no/fhs-xmlui/handle/11250/2721515

Jewkes, S. (2024, April 23). *The Future of Maritime Risk Management: Data Sharing Platforms*. Marine Information Solutions. https://mismarine.com/the-future-of-maritime-risk-management-data-sharing-platforms/

Joo, J., Kim, S.-S., Choi, J. W., Pak, S.-J., Ko, Y., Son, S.-K., Moon, J., & Kim, J. (2020). Seabed Mapping Using Shipboard Multibeam Acoustic Data for Assessing the Spatial Distribution of Ferromanganese Crusts on Seamounts in the Western Pacific. *Minerals*, *10*(2), Article 2. https://doi.org/10.3390/min10020155

Josso, P., Hall, A., Williams, C., Le Bas, T., Lusty, P., & Murton, B. (2023). Application of random-forest machine learning algorithm for mineral predictive mapping of Fe-Mn crusts in the World Ocean. *Ore Geology Reviews*, *162*, 105671. https://doi.org/10.1016/j.oregeorev.2023.105671

Liu, B., Liu, Z., Men, S., Li, Y., Ding, Z., He, J., & Zhao, Z. (2020). Underwater Hyperspectral Imaging Technology and Its Applications for Detecting and Mapping the Seafloor: A Review. *Sensors*, *20*(17), Article 17. https://doi.org/10.3390/s20174962

Lv, Z., Lv, H., & Fridenfalk, M. (2023). Digital Twins in the Marine Industry. *Electronics*, *12*(9), Article 9. https://doi.org/10.3390/electronics12092025

Mascareñas, D. D., Ballor, J. P., McClain, O. L., Mellor, M. A., Shen, C.-Y., Bleck, B., Morales, J., Yeong, L.-M. R., Narushof, B., Shelton, P., Martinez, E., Yang, Y., Cattaneo, A., Harden, T. A., & Moreu, F. (2021). Augmented reality for next generation infrastructure inspections. *Structural Health Monitoring*, *20*(4), 1957–1979. https://doi.org/10.1177/1475921720953846

Mohamed, H., Nadaoka, K., & Nakamura, T. (2020). Towards Benthic Habitat 3D Mapping Using Machine Learning Algorithms and Structures from Motion Photogrammetry. *Remote Sensing*, *12*(1), 127. https://doi.org/10.3390/rs12010127

Papadopoulos, G., Kurniawati, H., Wong, L. J., & Patrikalakis, N. M. (2011). 3D-Surface Reconstruction for Partially Submerged Marine Structures Using an Autonomous Surface Vehicle. *Institute of Electrical and Electronics Engineers*. https://doi.org/10.1109/IROS.2011.6094966

Robert, K., Huvenne, V. A. I., Georgiopoulou, A., Jones, D. O. B., Marsh, L., D. O. Carter, G., & Chaumillon, L. (2017). New approaches to high-resolution mapping of marine vertical structures. *Scientific Reports*, *7*(1), 9005. https://doi.org/10.1038/s41598-017-09382-z

Rossi, P., Ponti, M., Righi, S., Castagnetti, C., Simonini, R., Mancini, F., Agrafiotis, P., Bassani, L., Bruno, F., Cerrano, C., Cignoni, P., Corsini, M., Drap, P., Dubbini, M., Garrabou, J., Gori, A., Gracias, N., Ledoux, J.-B., Linares, C., … Capra, A. (2021). Needs and Gaps in Optical Underwater Technologies and Methods for the Investigation of Marine Animal Forest 3D-Structural Complexity. *Frontiers in Marine Science*, *8*, 591292. https://doi.org/10.3389/fmars.2021.591292

Rossi, S., & Orejas, C. (2019). 39 Approaching Cold-Water Corals to the Society: Novel Ways to Transfer Knowledge. In C. Orejas & C. Jiménez (Eds.), *Mediterranean Cold-Water Corals: Past, Present and Future: Understanding the Deep-Sea Realms of Coral* (pp. 473–480). Springer International Publishing. https://doi.org/10.1007/978-3-319-91608-8_39

Sauder, J., Banc-Prandi, G., Meibom, A., & Tuia, D. (2024). Scalable semantic 3D mapping of coral reefs with deep learning. *Methods in Ecology and Evolution*, *15*(5), 916–934. https://doi.org/10.1111/2041-210X.14307

Venegas-Li, R., Levin, N., Possingham, H., & Kark, S. (2018). 3D spatial conservation prioritisation: Accounting for depth in marine environments. *Methods in Ecology and Evolution*, *9*(3), 773–784. https://doi.org/10.1111/2041-210X.12896