Revolutionizing Marine Computer Vision

Marine computer vision remains inherently challenging due to the scarcity of annotated training data, hindering the development of accurate algorithms. To bridge this gap, Atlantic Tech & Candy has specialized in the creation of large-scale, high-quality synthetic subsea image datasets. In this whitepaper we showcase the efficacy of this innovative approach by employing it to detect and identify marine growth on ship hulls, underscoring its transformative potential in advancing underwater image analysis and maritime applications.

Use case: AI-based Detection of Biofouling on Ship Hulls

Every object that is in the ocean for a longer period of time is colonized by marine organisms. These organisms range from single-celled organisms (microfouling/slime) to soft fouling such as algae and sponges to hard fouling such as barnacles, mussels and calcareous tube worms [1].

In the case of ship hulls, fouling causes a significant increase in greenhouse gas emissions. Even a thin biofilm can increase emissions by up to 25%. Hard fouling increases emissions by 50% or more [2]. In addition to increased fuel consumption, fouling on ship hulls also poses the risk of invasive species being introduced [3].

In offshore installations, fouling leads to increased mechanical stress due to additional weight and increased flow resistance during tidal currents [4].

For this reason, regular monitoring and cleaning of these structures is essential. Historically, these tasks were carried out exclusively by divers, apart from occasional cleaning in dry docks. This is time-consuming, costly and — especially in offshore areas — dangerous for the divers.

Recently, remote-controlled underwater drones (ROVs) have been increasingly used for inspections. In addition, there are already remote-controlled cleaning robots for ship hulls. In the long term, the aim is to have these tasks carried out by fully autonomous robots (AUVs) [5]. This development towards autonomous systems promises a more efficient, cost-effective and environmentally friendly management of underwater structures.

One of the tasks in this process is to assess the fouling in order to decide whether to clean the structure. This assessment is carried out using images of the hull taken by divers or ROVs. The BIMCO 'Industry Standard on In-water

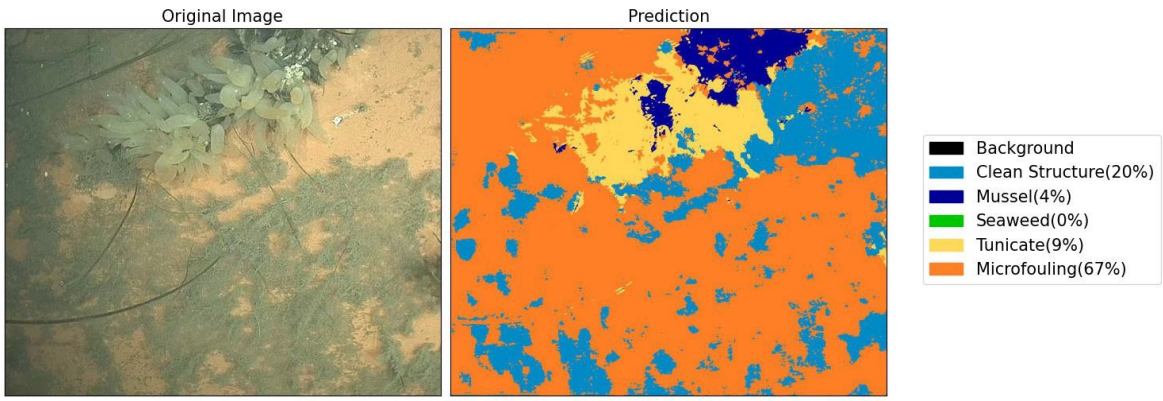

Figure 1: Our system adeptly analyzes original ship hull images, accurately discerning both the type and extent of biofouling present

Cleaning with Capture' defines the requirements [6]. According to this standard, microfouling (biofilm), identified species and percentage of fouling (soft and hard) must be recorded. Today, this is largely a manual process [7].

Atlantic Tech & Candy is dedicated to automating the assessment process of marine growth on ship hulls. Initially, we develop a sophisticated computer vision model adept at detecting and classifying various types of marine growth. Illustrated in Figure 1 is a prime example wherein the system automatically evaluates an original image showcasing marine growth on a ship hull. The model predicts a corresponding class for each pixel, such as clean structure, microfouling, or mussel, and subsequently calculates the percentage of coverage based on these predictions.

The remarkable outcomes demonstrated in this instance are made achievable through our innovative synthetic subsea imagery methodology. In the subsequent sections, we will elucidate our approach in more detail. Furthermore, additional examples can be found at the end of this document.

It's noteworthy that our system's versatility extends beyond the showcased application. It can seamlessly adapt to other use cases, such as identifying specific invasive species or assessing marine growth on offshore structures.

Marine Computer Vision

The Core Task

To get a better understanding of what we want to achieve, we need to look at the core task of the computer vision model. Figure 2 outlines this task. As input we have an image exhibiting marine growth on a ship hull. We want to get an estimate of the type and amount of biofouling. This requires a computer vision model that implements so called semantic segmentation.

The core task of semantic segmentation involves categorizing each pixel in an image into a specific class, thereby providing a detailed understanding of the scene's composition and structure. This technique enables precise delineation of objects and regions within an image,

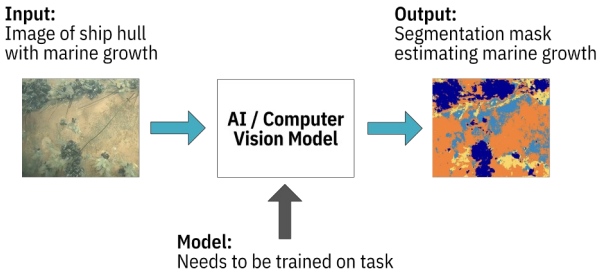

Figure 2: The core task of semantic segmentation

facilitating applications such as calculating the percentage of coverage by each biofouling species. The input image is processed by the model, resulting in a semantic segmentation mask as output.

To successfully execute semantic segmentation, the model must undergo specialized training tailored to this precise task.

The Training Process

This training process involves exposing the model to annotated datasets, where each pixel is labeled with its corresponding class (Figure 3). Through iterative learning, the model gradually refines its ability to accurately assign semantic labels to pixels, enabling it to discern intricate details and boundaries within images. This trained model can then be deployed to perform semantic segmentation on unseen data.

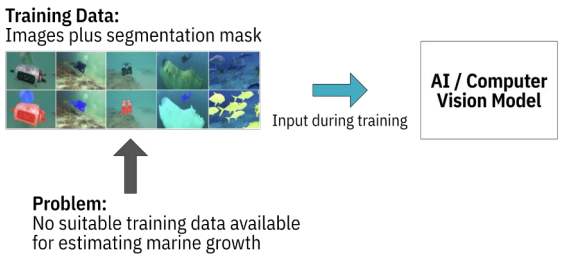

Figure 3: For training, images and the corresponding segmentation masks have to be provided

Central challenge: lack of annotated image data

The central challenge in underwater image recognition (especially for the assessment of

ship hulls) is the lack of annotated image data [7], [8].

The training of image recognition systems requires a large amount of training data. To ensure that the image recognition system is able to make reliable predictions, the training data must cover a wide range of possible situations. The underwater world is especially challenging in this regard, due to the complexity of species, light attenuation by the water, and noise created by marine snow.

Hull shape	Water type	Species
Valves, outlets, etc.	Absorption and scattering	Biofouling density
Coating	Natural lighting	Marine snow
Damages / markings	Artificial lighting	Camera position and angle
Image resolution	Water surface (refraction / reflexion)	Camera field-of-view

Table 1: Example parameters to be covered by dataset

Table 1 provides examples of parameters that need to be taken into account by the image data in the case of marine biofouling. It is crucial that this training data contains a variety of examples from different environments, lighting conditions and biofouling patterns to improve the robustness and accuracy of the system. Figure 5 gives a small impression of possible fouling situations.

The acquisition of original image data by divers or ROVs that cover the necessary parameter ranges is very time-consuming and expensive. Added to this is the necessary (manual) annotation of the data. While only very simple objects were segmented in the example in Figure 6, Figure 4 shows examples of real vegetation on a ship's hull. Here, pixel-precise annotation is extremely time-consuming, if not impossible, as the individual types of vegetation are not clearly delineated (black-greenish biofilm, green algae, white barnacles and tube worms).

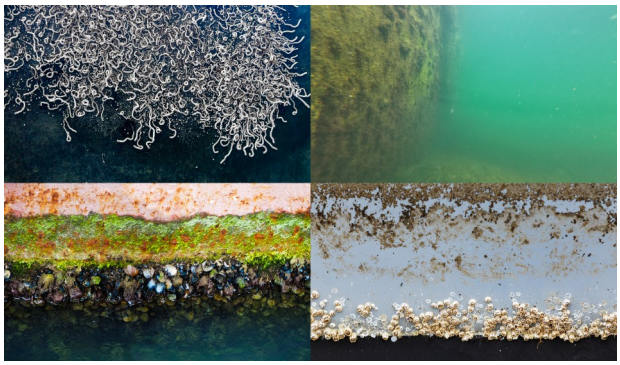

Figure 5: Examples of marine growth (original imagery)

Figure 6: Example images with segmentation mask [8]

The effort required to capture and manually annotate thousands of images has so far prevented the creation of corresponding image datasets. There has only been an attempt to classify images of ship hulls into 3 classes (clean, light, heavily overgrown) and to evaluate them automatically [9]. However, the images were classified as a whole and not each pixel. In addition, the data set is not freely available.

Due to the lack of annotated image data, the development of robust algorithms capable of accurately interpreting underwater images remains a challenging task.

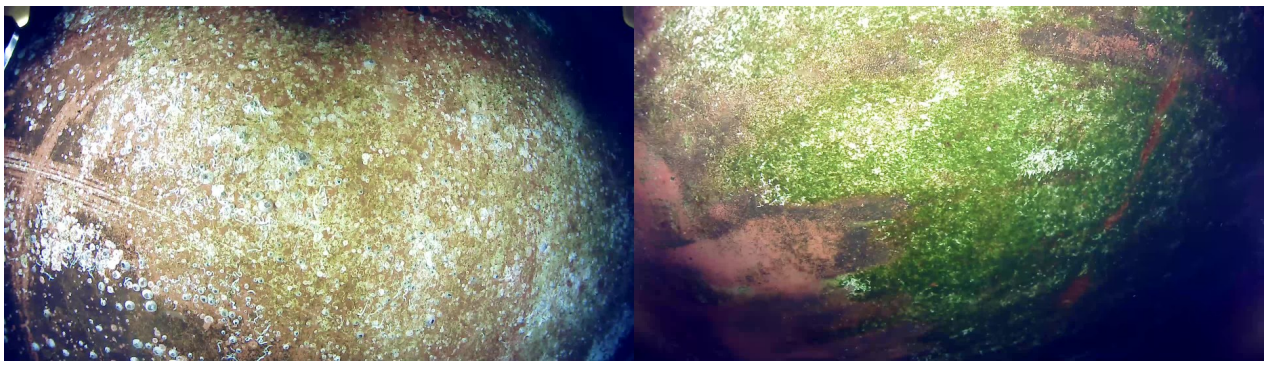

Figure 4: Example of real marine growth on a ship hull. Manual, pixel-perfect annotation is practically impossible.

Our Approach: Synthetic Underwater Image Data

As an alternative to real image data, synthetic image data is now used in many image recognition scenarios. For the subsea space, the approach has been proposed in [10], but it has not been implemented on a large scale so far.

Synthetic image data are digital images that are not taken directly from real scenes or events, but are generated using computer graphics techniques. These techniques can be used to create realistic simulations of scenes, objects or events that could exist in the real world. Synthetic image data is often used in various areas of research and development, particularly in the field of machine learning and image recognition.

To generate synthetic imagery, usually a scene is modeled in some 3D environment. From there photo realistic images are rendered (Figure 8). The generation of synthetic image data must not be confused with generative AI approaches.

The creation of synthetic image data makes it possible to generate large and diverse datasets that can be used for training algorithms and models. These datasets can often be created faster and cheaper than real datasets as no physical images are required. Synthetic image data can also be used to model specific scenarios or edge cases that may rarely occur in real data, helping to improve the robustness of algorithms.

As an innovative pioneer, Atlantic Tech & Candy specializes in the creation of realistic synthetic underwater images. This specialization allows us to simulate diverse underwater environments with remarkable precision and provide

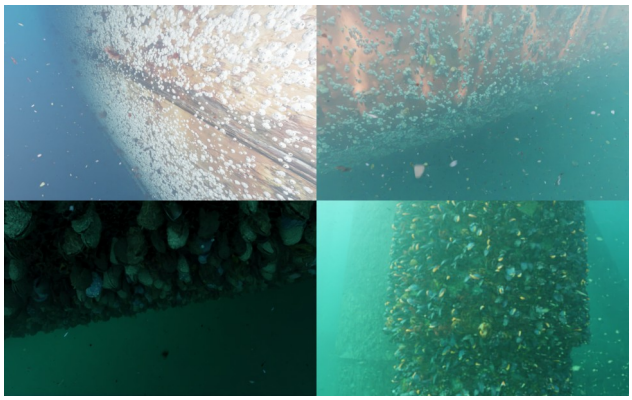

Figure 7: Example of synthetic imagery simulating different water types and lighting conditions

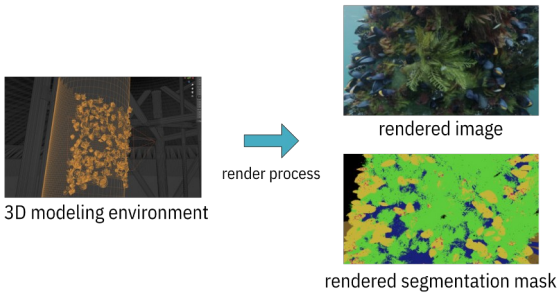

Figure 8: Conceptual process of generating synthetic images

valuable data for training and evaluating image processing algorithms in marine environments. With complete control over parameters such as water type, structure, species and lighting conditions, we are able to quickly adapt the environment to changing requirements and new scenarios. Figure 7 provides some examples of different water types and lighting conditions.

In addition to generating realistic images, synthetic image data has the advantage of being automatically annotated. In our case, semantic segmentation masks are thus generated automatically. Figure 10 and 9 show examples of rendered images including the corresponding segmentation masks.

Figure 9: Render of a hull with microfouling and balanus, segmentation mask (blue: clean hull, turquois: microfouling, red: balanus)

We use the open source tool Blender to generate the synthetic image data. Figure 8 shows the model of an offshore installation with simulated biofouling in Blender. The process in which a 2-dimensional image is generated from the 3D environment is called rendering.

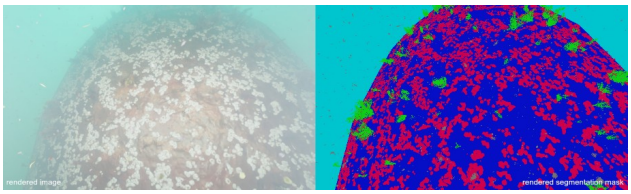

Figure 10: Render of a ship bow with biofouling, segmentation mask (blue: clean hull, light blue: water surface, red: balanus, green: algae)

Conclusion

Through our innovative synthetic image approach in marine computer vision, we achieve substantial enhancements in automatically assessing the biofouling status of ship hulls. By generating synthetic underwater imagery, we augment the diversity and richness of our training data, enabling more robust and accurate detection and classification of biofouling. This breakthrough empowers us to provide comprehensive and timely evaluations of ship hull conditions, facilitating proactive maintenance and conservation efforts in maritime environments. Additionally, our methodology holds promise for applications beyond ship hull assessment, spanning areas such as marine ecosystem monitoring and underwater infrastructure inspection.

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Acknowledgments

Original imagery 1,11,12,13 courtesy of Blue Atlas Robotics ApS, Denmark.

Original imagery 4 courtesy of Posicom AS, Norway

Appendix: Additional Examples

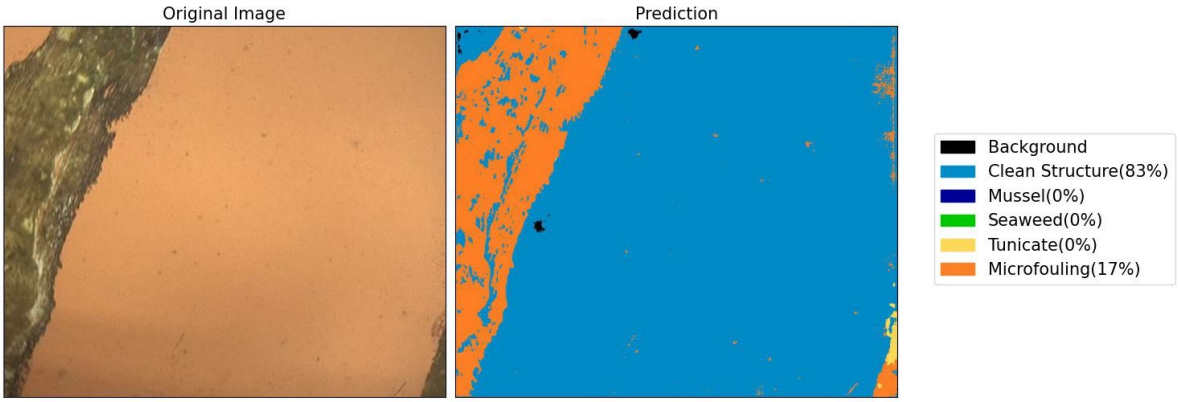

Figure 11: Microfouling on damaged coating

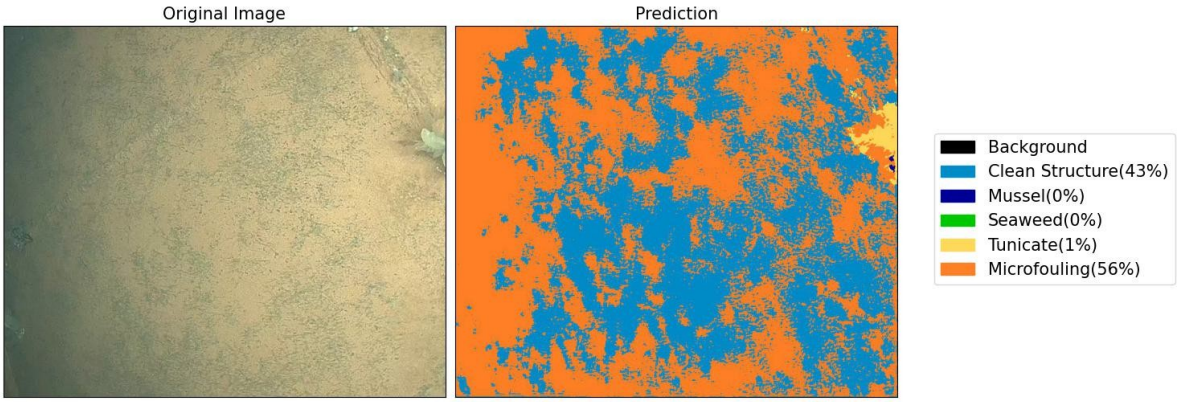

Figure 12: Mainly thin layer of microfouling

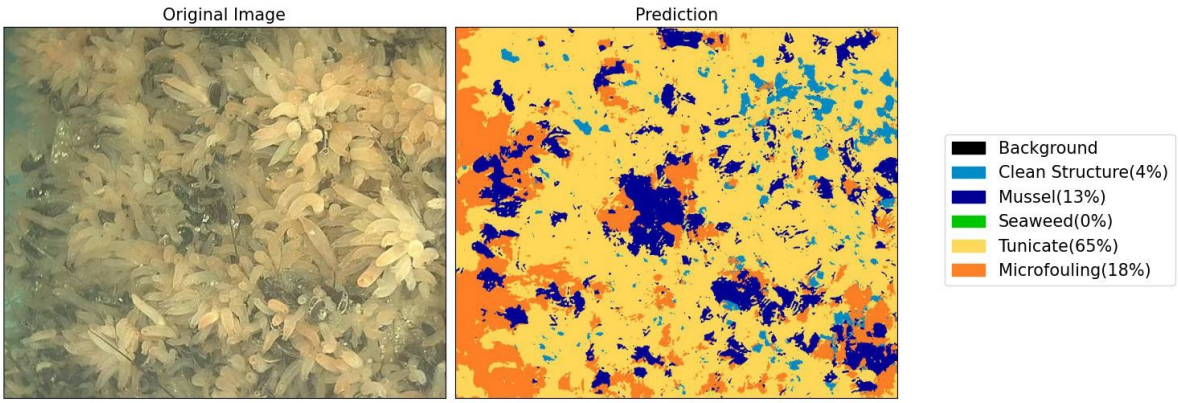

Figure 13: Fully covered surface