

# Extended Abstract: Physics based simulation of autonomous bubble detection based on visual and acoustic sensing

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## 1 Introduction

The process of testing underwater systems can be both costly and time-consuming. In order to assist researchers in the evaluation of their systems, a variety of simulations have been developed[CVL14][CSS24]. However, some of these simulations are deficient in terms of physical correctness and visual quality, and are not readily accessible to non-expert users or non-programmers. In order to achieve an optimal balance between physical correctness, visual quality and user-friendliness, it would be beneficial to utilize a game engine, such as the Unreal Engine. The Unreal Engine offers a number of advantages over other game engines, including high-quality visuals and a potentially user-friendly interface for non-programmers. The engine's "Blueprints" feature, a visual scripting system, provides a visual interface that allows non-experts to develop or extend existing systems.

A number of underwater simulations have already been developed for the Unreal Engine, but some of them lack the necessary features [MSH19] and/or physical correctness[GJY13][PLN<sup>+</sup>22][SCB<sup>+</sup>22]. The aim of this paper is to create a simulation of an automatic underwater bubble detection system using the Unreal Engine as the engine. To achieve this, a simulation of a camera and a forward-looking sonar has been developed, which balances the physical correctness, the visual qualities and the ease of use.

In order to test the results of the simulated environment, an automatic bubble detection system has been developed. This system is capable of detecting bubble sources on both camera images and sonar images. Based on this system, two U-Net models have been created which are able to detect such bubble sources on those images. As the U-Net is not integrated into the Unreal Engine, the robotic operating system (ROS) has been employed in order to release those images.

The following sections present an overview of the simulation process, including a discussion of its physical correctness, an explanation of the simulation environment, and a detailed description of the sensor simulation. Subsequently, the results will be presented. In addition, a comparison will be made between U-Net models that have been trained on pure real data and those that have been trained on a combination of synthetic data and real data. The final section will comprise a summary of the conclusions drawn.

## 2 Simulation

The objective of this paper is to identify the sources of methane bubbles through the utilisation of acoustic and visual sensing techniques. To achieve this, a camera and a sonar must be developed. In order to accomplish this objective, it was necessary to create an appropriate environment. For this, a 50x50 meter area was prepared, in which an underwater vehicle is able to navigate. To create a more accurate and realistic scene, some elevations and indentations have been added. The bottom was textured to resemble sand, and small rocks were added. The Unreal Engine offers a tool for sculpting, which are accessible to users without expertise in landscaping. Additionally, the Unreal Engine provides a connection to Quixel, a source of high-quality 3D assets and textures. To simulate the water, the Unreal Engine's built-in water system was used. A graphical user interface allows users

to alter the water color and transparency at runtime in order to simulate different environments. Invisible walls are used to delineate the boundaries of the area. Upon reaching these walls, the user is teleported back into the underwater environment, creating the illusion of unlimited driving distances.

In an effort to simulate the bubble plumes, an object is created which is capable of generating bubbles at random positions within a predefined area. In order to create the effect of bubbles rising upwards, another object is generated which floats in this direction. A noise effect is added to this direction, as well as a fixed value representing a ocean current. The bubble object is programmed to die after a specific time. As the area in which bubbles are generated is relatively small, and the direction in which they are floating is random and increases in dispersion over time, the result is a plume-like structure.

The Unreal Engine scene capture component is used to simulate the camera, which can be attached to the vehicle and is able to create images. The user is able to modify the field of view and brightness via the graphical user interface at runtime. Due to performance issues with exporting the images, the camera is only programmed to capture the scene once every three seconds. Another camera has also been implemented which creates labelled segmentation masks. The rationale behind this is that those synthetic images could be used to expand datasets, given that it is more straightforward to use simulation software than to collect real data. Furthermore, the simulated data is already labelled.

A new object has been created for the sonar, which employs ray tracing to simulate the sound wave. Upon contact with the sea floor, stone, bubbles or similar, each ray is subjected to a series of calculations designed to ascertain the reflected intensity. These calculations employ a range of equations, including those related to attenuation [MSH19], the target strength [Car77], the resonance frequency of bubbles [DME<sup>+</sup>18], the speed of sound in water/methane [MSH19] [FEI89], the speed of sound in bubbly water [RJR<sup>+</sup>22], volume backscattering [MSH19], and bottom backscattering [MSH19]. The aforementioned equations are calculated upon each impact. The OpenCV plugin for the Unreal Engine is used for the generation of sonar images.

### 3 Results

This section presents the results, which are illustrated with images and accompanied by an explanation. Furthermore, the synthetic images are discussed, with reference to the training of U-Net models using a pure dataset and a mixed synthetic dataset. The structure and color code of the synthetic sonar

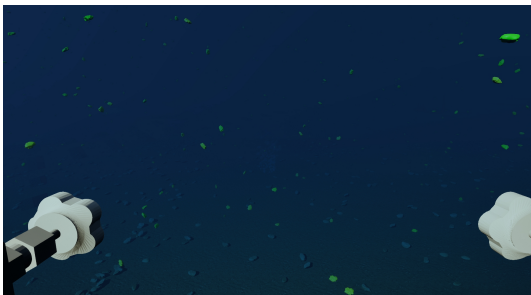


Figure 1: Synthetic camera Image

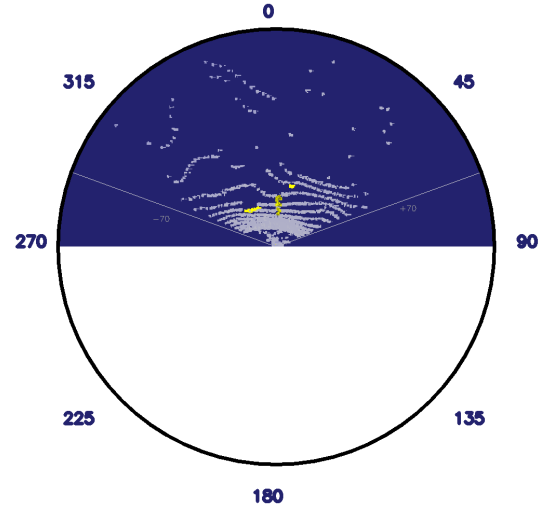


Figure 2: Synthetic Sonar Image

images are derived from those of the real sonar images, which are also employed for training the U-Net models. As no camera images were provided, the camera U-Net model is solely trained on synthetic images. Some preprocessing methods, such as CLAHE and MOG2, are also applied to these images

to facilitate the segmentation model.

To test the usefulness for the synthetic images different sonar segmentation models are trained and compared:

Dice	IoU	Precision	Recall	F1	Pixel Accuracy	Model
0.689217	0.543601	0.557493	0.952103	0.689216	0.999496	Model ManyRealSonar
0.740598	0.604994	0.666334	0.876612	0.740597	0.999513	Model ManySynthMix
0.000000	0.000000	0.000000	0.000000	0.000000	0.999372	Model SmallRealSonar
0.519512	0.396087	0.639431	0.482763	0.519511	0.999478	Model SmallSynthMix

Table 1: The ManyRealSonar set comprises 270 genuine sonar images, while the ManySynthMix set includes 270 genuine sonar images and an additional 310 synthetic images. The SmallRealSonar set contains 45 genuine sonar images, and the SmallSynthMix set comprises approximately 44 genuine images and 310 synthetic images.

Each model was tested on 100 images, of which 40 were genuine and 60 were synthetic. As the majority of scores are higher, except for the recall, it can be concluded that the synthetic images are useful for making the model more robust. Additionally, it demonstrates that the synthetic images can be employed to augment the quantity of data, thereby assisting the model in detecting patterns, as evidenced in SmallReaSonar and SmallSynthMix.

## 4 Conclusion

As part of this project, an underwater simulation was created in the Unreal Engine. To enhance the simulation’s physical correctness, various physical aspects were incorporated, particularly for the sonar simulation. The Unreal Engine’s flexibility and accessibility to non-expert users facilitate the incorporation of new features, thus enabling the expansion of the simulation. Additionally, it was demonstrated that synthetic images have a beneficial impact on the training of segmentation models.

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