Visual SLAM with Real-Time Image Enhancement for Autonomous Underwater Vehicles

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Abstract

In recent years, visual Simultaneous Localization and Mapping (SLAM) methods have shown significant performance, accuracy, and efficiency in autonomous robotic navigation. Research has demonstrated that visual SLAM is capable of outperforming traditional methods of navigation with lower cost. Recently, research has been done on the use of visual SLAM for use by autonomous underwater vehicles (AUVs). The highly unstructured and uncertain nature of underwater environments presents several challenges for robotic navigation, such as low contrast and color distortion. This work investigates the effects of real-time underwater image enhancement on visual SLAM methods for use in AUVs. This work combines DeepSeeColor, a novel underwater image enhancement method, with a popular visual SLAM method, ORB-SLAM3. It is hypothesized that the number of features will increase in the enhanced images, resulting in a more accurate, robust SLAM method. The results of this work may lead to improved navigation for AUVs in unstructured underwater environments.

I. Introduction

Several studies [1], [2] have been conducted on the utilization of simultaneous localization and mapping (SLAM) for robots operating in underwater environments. Two of the most commonly used localization methods of AUVs are dead reckoning and acoustic beacon positioning, but their complexity and expensive instrumentation create barriers to their use. Compared with inertial navigation and acoustic beacon positioning, SLAM is a much more affordable method. Since good video footage or images are core components of most ocean scientific research, research AUVs tend to be outfitted with high-output lighting systems and broadcast-quality cameras. This provides excellent conditions to use vision for precise positioning and navigation of underwater robots [2].

Underwater environments present several unique challenges to visual sensing and navigation, such as light refraction, absorption, and scattering from suspended particles in the water. Images also tend to have a blue or green hue to them, and this effect worsens as depth increases [7]. This can have negative effects on AUVs relying on visual SLAM for navigation, as the image quality directly affects feature extraction [8].

II. Problem Description

This project combines a visual SLAM method and a state-of-the-art image enhancement model to allow for more precise navigation of robots operating in underwater environments. The few research papers on this subject show that the accuracy of underwater SLAM methods is improved when combined with image enhancement [8], [9], [10]. Many different SLAM methods have been tested for underwater use [1]. ORB-SLAM3 [12] was selected for this project since its performance in underwater scenarios has been tested [13] and can serve as a baseline. ORB is an efficient alternative to other feature descriptors such as SIFT and SURF in terms of invariance to changes in viewpoint and illumination [13]. ORB-SLAM3 is a feature-based, tightly integrated visual-inertial SLAM system that fully relies on Maximum-a-Posteriori (MAP) estimation. The result is a system that operates robustly in real time in indoor and outdoor environments [12].

For the image enhancement, DeepSeeColor, a recently developed method, was selected. DeepSeeColor combines a state-of-the-art underwater image formation model with the computational efficiency of deep learning frameworks. This enables efficient color correction for underwater imagery *in situ* onboard autonomous underwater vehicles [11]. It is the first method to have developed robust, physics-based underwater color reconstruction methods intended to run onboard an AUV's highly constrained computational resources in real-time. The DeepSeeColor method estimates the backscatter and attenuation parameters of the underwater image formation model from [29] using a sequence of two convolutional neural networks. The networks are trained under self-supervision using the captured image and range map. This training process can take advantage of highly energy-efficient deep learning hardware accelerators increasingly found onboard autonomous platforms.

Due to lack of access to an AUV (and lack of a suitable location to operate it), it was decided to run this experiment using a dataset of underwater images. The dataset used must meet the requirements of both ORB-SLAM3 and DeepSeeColor. ORB-SLAM3 requires the images to be sequential and also needs the intrinsic camera parameters [12]. DeepSeeColor requires a directory of RGB or BGR images and a directory of corresponding single-channel depth images [16]. Finding a dataset that meets these requirements proved challenging. In the end, the D1 subset of the Sea-Thru dataset [20] was selected. The Sea-thru dataset was used by Jamieson et. al. to evaluate the performance of DeepSeeColor [11]. This dataset comprises 633 images depicting a coral reef scene taken by a ROV equipped with a downward-facing monocular camera. It includes depth maps corresponding to each image, and also provides the camera and lens used (Sony α7R MKIII and Sony FE 16-35mm f/2.8GM, respectively). Using the specifications from the manufacturer [30], the camera intrinsic parameters required for ORB-SLAM3 were calculated.

For this project, the original image dataset was prepared and run on ORB-SLAM3. Results were collected in the form of maximum, minimum, and average number of feature matches for a selected set of images. The dataset was then run through DeepSeeColor, and the enhanced images were also run on ORB-SLAM3. The feature matches were collected again, and compared to the results from the original, unenhanced images.

III. Related Work

Vision-based SLAM for underwater robots has been the topic of several research papers [3], [4], [5], [6]. The challenges facing underwater visual SLAM and the potential benefits of image enhancement on performance were investigated by Grimaldi et. al. [14]. Drews Jr et. al. developed a visual SLAM algorithm using SIFT and saw good performance for feature mapping, even with a large number of false correlations [3]. Pi et. al. [31] implemented a visual SLAM system for a stereo camera using SURF for feature matching and fusing features coordinates and AUV pose with an Extended Kalman Filter. Hidalgo et. al. ran a previous version of the ORB-SLAM algorithm, ORB-SLAM2, in a structured underwater environment [13]. It was found that ORB-SLAM performed well, but struggled with issues such as dynamic lighting, moving objects, and low-texture environments.

Much research has been done on underwater image enhancement. Looking at more traditional methods, Chiang et. al. introduced an algorithm for wavelength compensation and image dehazing to handle light scattering [23]. Ancuti et. al utilized fusion techniques to introduce a novel approach that is able to enhance underwater images based on a single image, as well as videos of dynamic scenes [22]. Fu et. al introduced a method using retinex theory to enhance underwater images, as well as other kinds of degraded images such as sandstorm images [25].

DeepSeeColor is heavily based on the Sea-Thru algorithm, introduced by Akkaynak and Treibitz [19]. Sea-Thru uses an underwater image formation model to estimate attenuation and backscatter, and achieved very good results for color recovery and reconstruction, but suffered from significant computational complexity.

While recent years have witnessed the significant advancement of deep learning in low-level vision problems, the performance and amount of deep learning-based underwater image enhancement methods have advanced somewhat slower. Underwater image formation models depend on specific scenes and lighting conditions and are even related to temperature and turbidity. Thus, it is difficult to synthesize realistic underwater images for training Convolutional Neural-Networks (CNNS). Further, the learned distribution by CNNs trained on synthetic underwater images does not always generalize to real-world cases [24]. However, deep learning for underwater image enhancement shows promise as the field advances. Recently, advancements have been made using Generative Adversarial Networks (GANS) for underwater image enhancement. Guo et. al. had good results using a GAN but found that their model failed to generate aesthetically pleasing synthesized underwater images [26]. Islam et. al. also achieved good results for underwater image enhancement using a GAN but found that it was not very effective at enhancing low-contrast or texture-less images [7]. A deep learning approach was taken by Alves et. al. by using a fully convolutional network to perform semantic segmentation on underwater images [4].

Another issue with deep-learning methods is computation cost. Most existing models fail to ensure fast inference on single-board robotic platforms, which limits their applicability for improving real-time visual perception. FUnIE-GAN, developed by Islam et. al., is capable of real-time performance on a single-board computer but balances a trade-off between robustness and efficiency, which limits its performance to a certain degree [7].

While plenty of research has been done on visual SLAM for underwater environments and underwater image enhancement, there are relatively few works that combine the two. Huang et. al. combined ORB-SLAM with their Retinex theory method for image enhancement and found that the enhanced images resulted in more key points and less frames lost when running ORB-SLAM [8]. Zheng et. al. also saw increased performance in ORB-SLAM2 and ORB-SLAM3 in the form of feature matching when combined with GAN-based image enhancement [9]. Histogram equalization was used by Liu et. al. to enhance grayscale underwater images from the AQUALOC dataset [15], and also saw an increase in feature matches when the images were run on ORB-SLAM3 and found that the robustness and accuracy of ORB-SLAM3 was improved when the enhanced images were used [10].

IV. Results and Insights

Several preliminary steps had to be taken before running ORB-SLAM3 on the Sea-Thru dataset. First, the camera intrinsic parameters were calculated using the camera and lens specifications from the manufacturer's website [30]. The camera matrix was calculated using Equation 1 below:

$$C = \begin{bmatrix} fx & 0 & cx \\ 0 & fy & cy \\ 0 & 0 & 1 \end{bmatrix} \tag{1}$$

The parameters cx and cy are the x and y coordinates of the principal point (half of the image width and height, respectively). The parameters fx and fy are calculated according to Equations 2 and 3 below:

$$fx = \frac{Wf}{s_W} \quad (2)$$

$$fy = \frac{Hf}{s_H} \quad (3)$$

Where W and H are the image width and height, respectively, s_W and s_H are the sensor width and height, respectively, and f is the focal length.

A vocabulary file also had to be created for the dataset of images. ORB-SLAM3 uses a bag-of-words approach to create a vocabulary of words which can be used for place recognition and loop closing detection. This works by building a vocabulary tree that discretizes a binary descriptor space and uses the tree to speed up correspondences for geometrical verification [17]. The vocabulary is used to convert a set of features into a set of visual words. The vocabulary included by Campos et. al. with ORB-SLAM3 was created from a very large dataset and works well for most indoor/outdoor environments [12]. However, it does not work well for special environments, such as underwater. Liu et al. [10] solved this problem by creating a new vocabulary from the dataset of images being used. A method for creating a bag of words from a sequence of images was created by [17, 18]. This method was used to create a vocabulary file from the images in the Sea-thru dataset.

ORB-SLAM3 also requires timestamps for each image in a timestamp file. These were not provided with the Sea-Thru dataset but were able to be calculated using the camera's frame rate. While not ideal, it proved adequate for the purpose of this experiment.

An enhanced version of the dataset was created by processing the images with DeepSeeColor. Google Colab was used for this, since DeepSeeColor requires a CUDA-capable GPU. A comparison of the original and enhanced images is shown below in Figure 1:

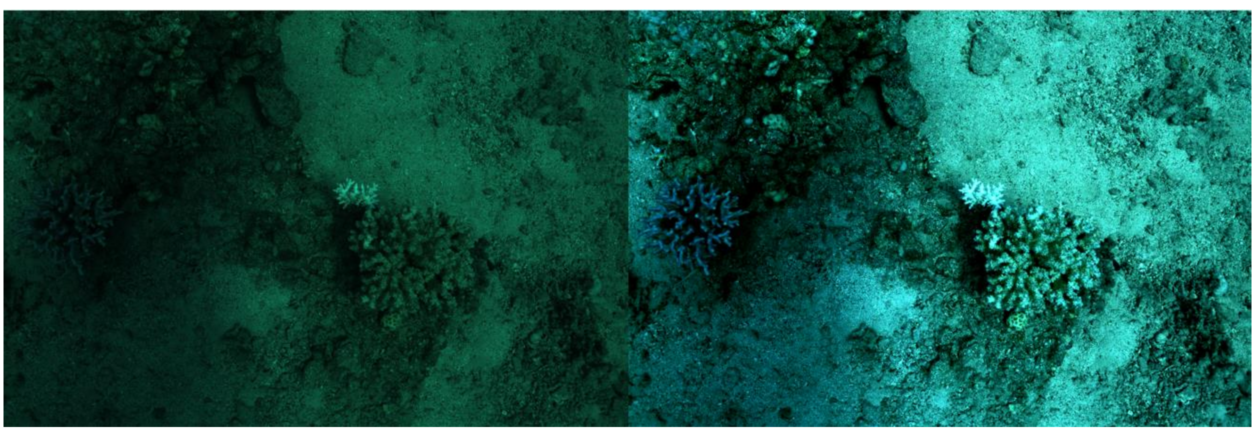

Figure 1: *Comparison of an original image of the Sea-Thru dataset (left) with the same image after enhancement with the DeepSeeColor algorithm (right)*

The parameters used for DeepSeeColor were the same as those used by Jamieson et. al. in their paper, since they also used the Sea-thru dataset [11]. The results acquired here are not the same as those in the

DeepSeeColor paper, as their results lacked the blue-ish hue seen in the enhanced image in Figure 1. It is possible that this issue is a result of running the code on Google Colab instead of using the command line, as originally intended. It could also be possible that the code has some bugs, which is to be expected since it was released very recently.

The original and enhanced images were then run on ORB-SLAM3. ORB-SLAM3 was not able to run through the entire dataset, losing track of the map after about 40-50 frames. This is possibly due to the relatively low frame rate of the camera used (10 fps). Each set was run three times, since ORB-SLAM3 is non-deterministic, and results were analyzed by the number of feature matches. The results of the three runs were averaged and a subset of thirty images was taken from the original and enhanced trials for further analysis.

Overall, an increase in the number of feature matches was seen in the enhanced images. The results are shown in Table 1 below:

Table 1: *Summary of results over 30 frames*

	Original	**Enhanced**
Max Matches	192	316
Min Matches	65	90
Average	127	174

Observing Table 1, a significant increase in feature matches can be seen in the enhanced images. This increase is particularly prominent in the darker regions of the images. This suggests that light level plays a significant role in feature detection and matching. This can be observed in Figure 2, below.

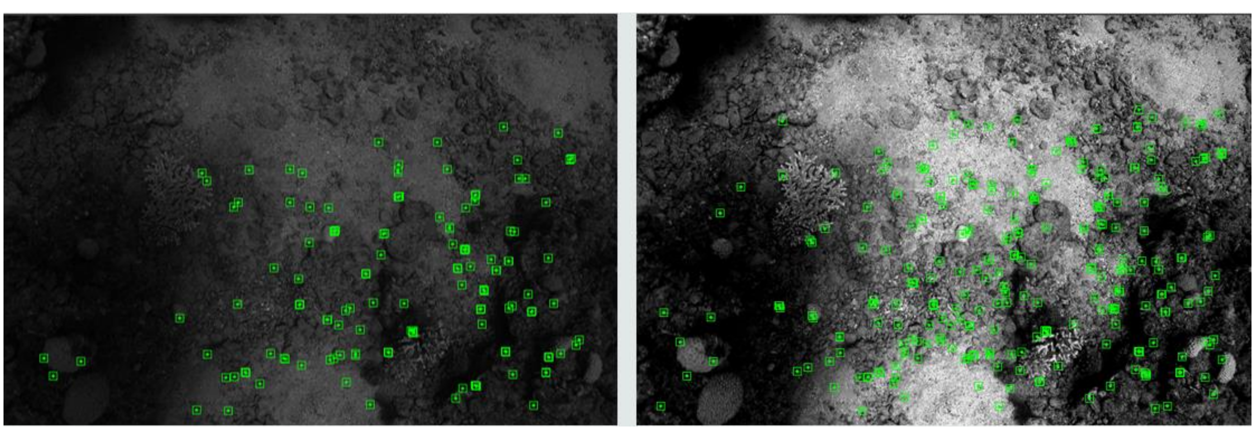

Figure 2: *Feature matches obtained by ORB-SLAM3 for the same image in the original dataset (left) and enhanced dataset (right)*

While the original dataset performed fairly well, a large number of incorrect matches, or false correlations, were observed. The enhanced images contained more matches on average along with more correct matches. To illustrate this, ORB feature extraction and matching was performed on a sequence of two images in each dataset using OpenCV. The results are shown in Figure 3.

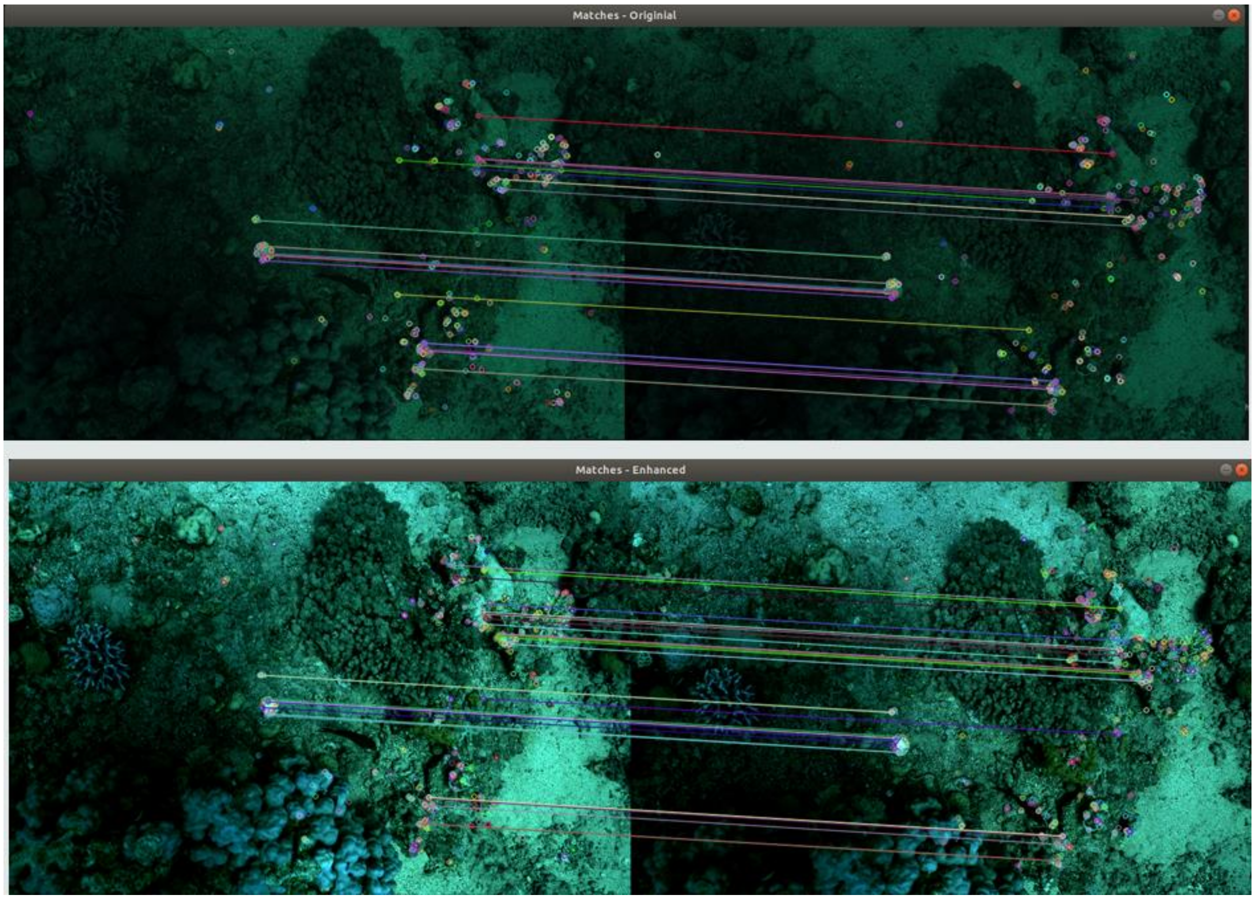

Figure 3: *ORB feature matching using OpenCV for two images in the original dataset (top) and enhanced (bottom). Only the first twenty matches are drawn for better viewing.*

While ORB-SLAM3 lost track of the map after a certain number of frames when running both the original and enhanced images, it was observed that it was able to go 5 – 10 frames further on average using the enhanced images. It was also able to get back on track and regenerate the map after losing position a couple times. These results agree with the findings of Liu et. al. and Zheng et. al.: enhanced images improve the robustness of ORB-SLAM3 in underwater environments.

While this project could not be run on an actual AUV to evaluate real-time performance, the combination of ORB-SLAM3 and DeepSeeColor should prove viable for real-time operation. Jamieson et. al. do not mention what specific hardware they used to evaluate DeepSeeColor, only that DeepSeeColor was able to correct up to 60 images per second and that it has significantly reduced computational complexity compared to other color-correction algorithms of similar performance [11]. ORB-SLAM3 has relatively low computation costs and is capable of running on lower-end hardware such as a Raspberry Pi [12]. It is probable to assume that given a board with CUDA capabilities, such as something from the Nvidia Jetson line, the combination of ORB-SLAM3 and DeepSeeColor should be able to offer real-time performance. However, this requires verification in future work.

V. Lessons Learnt

One lesson learnt from this project is that when dealing with experimental software, installation instructions should be followed exactly. If something was compiled on a specific version of Ubuntu or with a certain version of OpenCV or Python, do not assume it will work with a different version.

Another lesson is that when conducting research of this nature, things will go wrong, and a lot of troubleshooting will be required. In some cases, you may be the first person to attempt to solve a specific problem, in which case online resources will be of limited assistance. A lot of research and trial-and-error will be required to get around certain roadblocks, and even then, it may not work. It can be demoralizing to spend weeks trying to get past an issue, only for it to not work out.

VI. Problems Encountered

Several problems were encountered during the course of this project. The dataset ran very slowly, only processing around ten frames per hour. One possible reason for this is the custom ORB vocabulary. This vocabulary was created using only 633 images, while the original ORB vocabulary provided by Campos et. al. was created on a dataset consisting of tens of thousands of images. It is probable that using a much larger dataset to create a vocabulary will greatly improve the performance of ORB-SLAM3.

As a result of the ORB-SLAM3 algorithm failing to generate a complete map of the environment due to losing track of the map at certain points, metrics commonly used to evaluate SLAM performance, such as Absolute Trajectory Error and Root Mean Square Error, could not be calculated. A dataset of images taken by a camera with a framerate of at least 20 -30 frames per second would most likely alleviate this problem, due to a smoother transition between images.

Finding a suitable dataset was also a problem. The only dataset that could be found that met the requirements of both ORB-SLAM3 and DeepSeeColor was the Sea-Thru dataset. The images in this dataset were taken in relatively clear water with a low turbidity and relative lack of lighting changes, so these conditions could not be evaluated. It would have been ideal to observe performance in varying conditions. DeepSeeColor is an adaptive algorithm, and was designed to handle such changes in turbidity, lighting, etc., but it would have been best to see how it performs with ORB-SLAM3 in such conditions.

VII. Future Work

This project presents many options for future work on this concept. Using an AUV or ROV to collect and create a custom dataset of underwater imagery is one such option. This would also make running ORB-SLAM3 easier, as the camera parameters and specifications would be known.

As mentioned earlier in this paper, ORB-SLAM3 uses a bag-of-words approach to create a vocabulary of words which can be used for place recognition. A custom ORB vocabulary file was created for this project but was created from a dataset consisting of only 633 images. A possible option for future work is to create an ORB vocabulary for underwater scenarios, using a dataset consisting of tens of thousands of underwater images in various conditions. Experiments could then be conducted by using this new vocabulary with ORB-SLAM3 on a different underwater dataset to see if performance improves.

Another option for future work is to test the combination of DeepSeeColor and ORB-SLAM3 in underwater scenes with high turbidity or dynamic lighting. As mentioned above, these scenarios were not able to be evaluated with the Sea-Thru dataset.

Yet another option for future work is comparing the effects of using a stereo camera vs. monocular. Monocular SLAM is cheaper to implement, since only a single camera is needed, while stereo SLAM provides depth information. Setup is also simpler for the monocular case. Monocular cameras are also unable to determine the absolute scale of the mapped environment due to scale ambiguity and are also unable to provide depth perception. It can be hypothesized that the improved robustness and added depth perception provided by a stereo camera would produce more accurate results for visual SLAM algorithms. It would be interesting to test this on ORB-SLAM3, as it provides running modes for both monocular and stereo cameras.

Finally, another option for future work is to evaluate the effects of an underwater image enhancement/visual SLAM combination on object detection for tasks such as fish tracking, marine litter detection, or coral reef health monitoring.

VIII. Conclusion

In this paper, efforts are made to improve visual SLAM performance in unstructured underwater environments. The DeepSeeColor algorithm was used to enhance the images, and ORB-SLAM3 was run with both the original and enhanced images. It was found that more ORB features were able to be extracted from the enhanced images, which correlates to higher accuracy of pose estimation of the SLAM method. The results obtained in this paper are promising and reinforce the findings of prior research papers on this topic. Further work is recommended to verify the full extent of the increase in performance and real-time capability.

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