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Underwater Image Focus Determination and Calibration Using the Laplace Operator

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***Abstract*— Relying on RGB cameras for underwater robotics presents challenges, particularly due to varying light conditions that reduce image processing effectiveness. This work-in-progress paper explores image focus detection methods designed for dynamic underwater environments. We use the Laplacian operator to measure focus and evaluate its effectiveness through lab and underwater experiments with the Reach Alpha 5 manipulator arm. Our goal is to enable underwater robots to dynamically adjust camera positioning for clearer imaging. While effective in many scenarios, the method requires manual intervention due to the lack of standardized thresholds and reliance on raw Laplacian values. Future improvements, such as adaptive thresholding and normalization, could enhance robustness and applicability. This approach lays the foundation for real-time focus optimization in underwater robotics, benefiting autonomous inspection, manipulation, and exploration.**

I. Introduction

Underwater robotics relies heavily, among other modalities, on clear images for tasks like inspection, mapping, and manipulation [1], [2]. However, capturing sharp images underwater is challenging due to light scattering, refraction, and murky water conditions [3], [4]. These factors can blur images, making it difficult for computer vision systems to detect objects and estimate their positions accurately.

Traditional autofocus methods, designed for land-based photography, do not have considerations for the additional challenges in underwater environments [5]. To address this issue, we explore methods for determining the level of focus in image streams. More specifically, we employ Laplace transformations to detect image focus and to measure how rapidly pixel intensities change, which helps determining if an image is sharp or blurry. By integrating this focus detection into an underwater robot's control system, the robot can automatically adjust its position to get the clearest view, or switch between multiple sensors. Although a similar work uses Laplacian edge detection [6], our work focuses on the detection of level of focus in image streams. This can be specifically useful for decision making operations where the robot is equipped with multiple sensors. For instance, in a setup where the robot is equipped with a body camera and an alternative wrist camera, a decision-making algorithm can switch between cameras to increase efficiency.

To validate the effectiveness of our approach, we perform real-world experiments with a 5 DOF Reach Alpha underwater manipulator arm (by Reach Robotics) equipped with a camera mounted adjacent to its end effector. Using AprilTags for calibration and validation, we aim to improve the robot's vision and overall performance in underwater tasks.

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Fig. 1: Reach Alpha 5, a 5DoF underwater manipulator arm equipped with a mounted camera used in our experiments.

Our work-in-progress research not only enhances underwater inspection and manipulation but also has potential applications in other challenging environments, such as low-light or dynamic settings in aerial and industrial robotics.

II. Methodology

A. Overview of the Laplace Operator

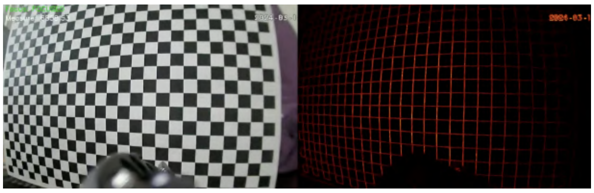
The Laplace Operator is commonly used for edge detection in image processing and computer vision [6]. The Laplacian of a grayscale image I is computed using:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (1)$$

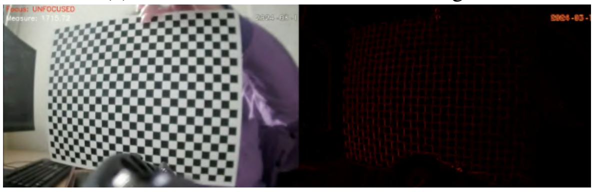
where it takes second order partial derivatives in the 2D Cartesian coordinate. For edge detection on images, an approximation of (1) can be formed into a square convolution kernel K. Applying this kernel to digital images highlights areas where the pixel intensity changes rapidly, thereby detecting edges. To measure image sharpness, we measure the variance of the Laplacian values as

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (L_i - \mu)^2 \quad (2)$$

where L_i represents the Laplacian value at each pixel i, μ is the mean of the Laplacian values, and N is the total number of pixels in the image. A higher variance value indicates a sharper image, while a lower variance suggests blurriness.



(a) In-focus frame with detected edges.



(b) Out-of-focus frame with detected edges.

Fig. 2: Focus analysis of a checkerboard at various distances.

B. Thresholding for Focus Determination

By allowing users to adjust control parameters and focus thresholds, this method can adapt to different lighting conditions and water clarity levels. This flexibility is crucial for applications such as underwater robotics, marine life monitoring, and archaeological explorations, where maintaining optimal focus is essential for object detection and scene analysis [7]. The visualization provides real-time feedback on focus variations, enabling improved image processing and decision making in dynamic underwater environments. We use a threshold value, δ, to classify whether a frame is in focus or not. For each experiment, we use a pre-defined threshold value. If the variance exceeds this threshold, the frame is considered focused. The Laplacian values computed are raw transform outputs and lack calibration to any standard focus metrics. Since there are no established norms for threshold values, users must adjust the parameters based on the environmental conditions such as lighting conditions. For example, while a threshold of 100 may work for well-lit scenes, darker images or those with complex content might require larger values. Consequently, the absolute variance values have limited standalone meaning. Future improvements could include (a) normalizing the Laplacian output relative to the mean intensity of the frame and (b) introducing adaptive thresholding that dynamically adjusts based on scene characteristics.

III. Experiments

In our experiments, we evaluate the effectiveness of applying the Laplacian variance-based focus detection method to a robotic platform in an underwater environment using the Reach Alpha 5 manipulator. This system features a camera mounted on a manipulator designed for underwater operations, offering an opportunity to optimize both positioning and focus in challenging environments.

A. Hardware Overview

The Reach Alpha 5 is a 5 Degree-of-Freedom (DoF) manipulator intended for underwater intervention. It features a camera mounted adjacent to the end effector, giving the robot flexibility in how it views objects and frames workspaces. We chose to use this for its adaptability to various scenarios and its robustness in underwater environments.

In future experiments, the manipulator will be mounted on a BlueROV, a six-thruster underwater robot intended for inspection, research, exploration and similar activities. We chose the BlueROV based on its capabilities and its easy integration with the Reach Alpha 5. When operating underwater, in order to deal with challenging conditions such as light scattering and refraction, achieving a sharp focus is critical, not only for capturing clear images, but also for ensuring reliable object detection and pose estimation. To tackle these issues, we aim at benefiting from the camera's mobility that allows for dynamic adjustments. In other words, the system can change its spatial position and depth in real time based on feedback from the focus metric computed via the Laplacian variance method. This adaptive approach ensures that the camera continually finds the optimal viewing angle and distance for inspecting a target object or workspace.

B. Image Focus Determination

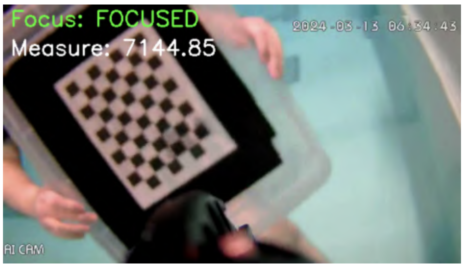
We conducted experiments using the Reach Alpha 5 camera both in the lab and underwater. Fig. 2 shows two instances of testing with a checkerboard using the Laplace edge detector, one in focus (top) and the other out of focus (bottom). The next set of experiments were performed underwater as seen in Fig. 3. Figs. 3b and 3a show instances of frames when the checkerboard in in focus and out of focus, respectively. The Laplacian threshold for the lab tests in Fig. 2 differs drastically from the threshold set in the underwater experiments. Fig. 3c shows a comparison of the focus measurement results between the two environments. The threshold for the underwater experiments needed to be set to higher values, highlighting the effects of lighting and contrast in underwater environment. If we keep a constant threshold value for the underwater experiments the image focus status changes frequently. In other words, the threshold values should be constantly adjusted during the operation based on the changes in the environment.

C. Underwater AprilTags Detection

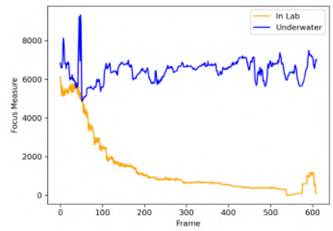
In our preliminary experiments, we deploy AprilTags underwater at various orientations and distances. AprilTags serve a dual purpose: They provide a quantitative, binary metric of image readability and offer a robust framework for pose estimation.

Two instances of our underwater tests are depicted in Fig.4. Fig. 4a shows a 50mm AprilTag at 0.44m. Although the tag can be detected successfully in this frame, this was the farthest distance before it becomes undetectable. Fig. 4b shows a 50mm AprilTag at 0.12m detected successfully. Our experiments indicates that this was an ideal distance to achieve best focus for this experiment. The graph in Fig. 4c shows the maximum view distance over the size of the AprilTags. The preliminary results suggest that the

(a) A sample frame where the checkerboard is out of focus.



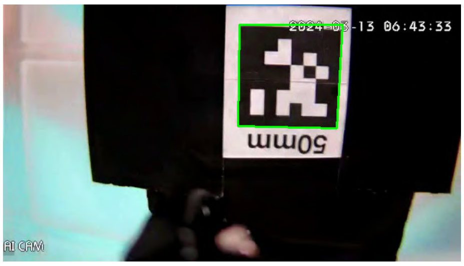
(b) A sample frame where the checkerboard is in focus.



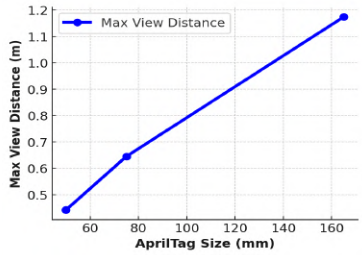
(c) Focus measure values in the experiment with checkerboard comparing results in the lab vs. underwater.

Fig. 3: Underwater focus measurement experiments on a checkerboard using the Reach Alpha camera.

(a) A 50mm AprilTag at 0.44m, the farthest distance before it becomes undetectable.



(b) A 50mm AprilTag at 0.12m, the ideal distance to achieve best focus.



(c) Maximum view distance measured against AprilTag size.

Fig. 4: Underwater AprilTag detection experiments using the Reach Alpha camera.

acceptable view distance is proportional to the level of detail required to recognize.

By analyzing the clarity with which AprilTags are captured under different conditions, we can correlate the focus metric with real-world performance. This calibration step not only validates our focus detection approach but also enhances the overall accuracy of the robotic system's perception module.

IV. Future Work Plans

The integration of focus detection into the robotic control loop is key. Our proposed approach involves a feedback mechanism by which the computed focus metric informs adjustments in the camera's pose. The capability of real-time adjustment is expected to significantly improve task performance, reducing errors in object detection and enhancing the precision of pose estimations. We anticipate that this integration will lead to:

- **Enhanced image quality** By continuously optimizing focus, the system should capture clearer images even under suboptimal underwater conditions.
- **Improved pose estimation** Better-focused images directly translate to more accurate detection of AprilTags, thereby improving the reliability of pose estimation.
- **Scalability to other domains** Although this use case focuses on underwater applications, the principles of this method could be extended to other challenging imaging environments, such as dynamic or low-light scenarios in aerial or industrial robotics.

Overall, this work aims to propose a robust framework for real-time focus optimization in dynamic environments, potentially setting the stage for more advanced underwater inspection and autonomous robotic techniques.

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References

[1] S. Cebollada, L. Payá, M. Flores, A. Peidró, and O. Reinoso, "A state-of-the-art review on mobile robotics tasks using artificial intelligence and visual data," *Expert Systems with Applications*, vol. 167, p. 114195, 2021.

[2] S. R. Ahmadzadeh, P. Kormushev, and D. G. Caldwell, "Autonomous robotic valve turning: A hierarchical learning approach," in *2013 IEEE International Conference on Robotics and Automation*. IEEE, 2013, pp. 4629–4634.

[3] K. Hu, C. Weng, Y. Zhang, J. Jin, and Q. Xia, "An overview of underwater vision enhancement: From traditional methods to recent deep learning," *Journal of Marine Science and Engineering*, vol. 10, no. 2, p. 241, 2022.

[4] L. Zhang, C. Li, and H. Sun, "Object detection/tracking toward underwater photographs by remotely operated vehicles (rovs)," *Future Generation Computer Systems*, vol. 126, pp. 163–168, 2022.

[5] S. Lin, Y. Zhang, L. Yu, B. Zhou, X. Luo, and J. Pan, "Autofocus for event cameras," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2022, pp. 16 344–16 353.

[6] X. Li, S. Yu, H. Gu, Y. Tan, and L. Xing, "Underwater image clearing algorithm based on the laplacian edge detection operator," in *International Conference on Artificial Intelligence, Robotics, and Communication*. Springer, 2022, pp. 159–172.

[7] I. Puente, H. González-Jorge, J. Martínez-Sánchez, and P. Arias, "Review of mobile mapping and surveying technologies," *Measurement*, vol. 46, no. 7, pp. 2127–2145, 2013.