State-of-the-Art Visual Measurement and Control Techniques for Underwater Robots: A Survey

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***Abstract*—Due to the unusual behavior of water medium in the unstructured and hazardous ocean environment, computer vision requires significant attention to challenges faced by underwater robots. This study examines the key challenges and methods employed in underwater visual measurement and control system along with advantages and limitations involved as imposed by the aquatic environment. A state-of-the-art underwater vision system includes a comprehensive visual sensing and control pipeline, as well as key challenges and the methods used to address them. Furthermore, advanced development prospects are reviewed, with an emphasis on sensor technologies and image processing advancements to promote real-world underwater vision applications.**

***Index Terms*—Computer Vision, Vision sensing and control pipeline, Image Processing, FPGA-based Vision System**

I. Introduction

Computer vision "Visual perception employing computers" [1] is an emerging and rapidly developing technology that originated in 1960, when researchers explored teaching computers about visualizing and interpreting their environment. Computer vision is an image understanding task that not only extracts useful information but also creates its three-dimensional scene [1]. Its primary goal is to develop computer models of the human visual system that depicts 3D visualization of the environment. Computer vision has advanced rapidly and is now widely employed in a variety of real-world applications including medical imaging [2], self-driving vehicles [3], augmented reality [4], security and surveillance [5], and robotics [6]. In robotics, computer vision plays a crucial role as it allows robots to visualize, analyze, and interpret their environment by employing sensors that receive real-time information from the surroundings and computer vision algorithms that analyze, recognize, and identify obstacles to regulate their motions.

Although visual measurement and control of robots, whether on-ground or underwater task, is an essential part of the system, maintaining vision resilience is critical in underwater vision-based control. In general, the acquisition of visual information (position and pose of the objects) obtained through sensors is referred to as visual measurement, whereas vision control is the management of its movements, which is followed by visual measurement. However, vision and control for underwater robots are different in research depth primarily depending on the applications.

Due to the unusual behavior of water medium in the unstructured and hazardous ocean environment in underwater robotics, computer vision encounters significant challenges. The fluctuating lighting conditions underwater, non-uniformity of light beams, and confounding noise from particles are some of the more general problems [7]. Furthermore, limited communication between underwater vehicles and surveillance systems [8], as well as limited energy and processing resources [9], are some of the difficulties that robotics encounters when using computer vision in underwater robots.

Underwater vision has increased considerably in recent decades due to advancements in technology. Autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) with vision have a wide range of applications in scientific research, environmental effects monitoring (EEM) in environmental risk assessment (ERA) [10], underwater exploration [11], and military operations.

This paper aims to develop a comprehensive overview of the visual sensing and control pipeline for underwater robots. Section II discusses the vision control pipeline. Section II-A surveys about Image Restoration Processes, Section II-B surveys the Image Noise Reduction processes, Section II-C surveys the Image Optimization Process, and Section II-D surveys the Motion Control processes along with different techniques used in the process and a comparison of different methods based on their advantages and limitations are presented. Section III covers a discussion on development prospects and potential advancements in this field. Section IV concludes the finding of this research along with potential future work.

II. Visual Sensing and Control Pipeline for Underwater Robots

This section presents a comprehensive approach to developing a visual sensing and control system for underwater robots. The proposed pipeline involves the integration of several visual processing techniques, such as image enhancement, feature detection, noise reduction, image restoration, and 3D reconstruction, with control algorithms to enable autonomous navigation and manipulation tasks. Over the years, several underwater vision systems have been developed to address and enhance the visual clarity of underwater images. Typically, underwater image processing (UIP) and analysis frameworks can be categorized into seven distinct types, each targeting a specific area.

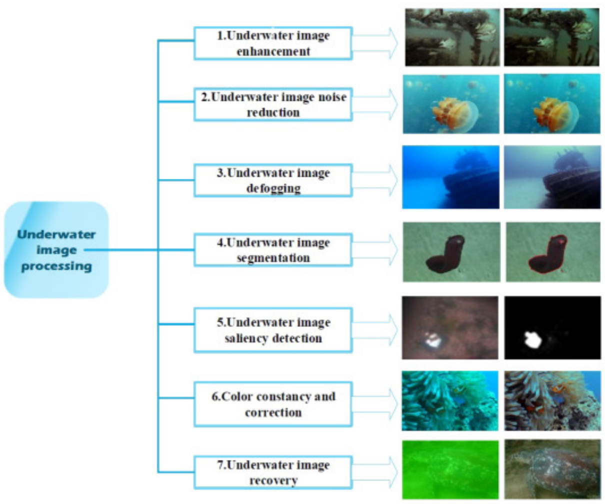

Fig. 1. [15]- Seven stages of underwater image processing framework

Image processing and preprocessing are critical components of many applications that rely on visual data, including underwater exploration, surveillance, medical imaging, robotics, and many others. These techniques help to improve the quality of images, extract meaningful information from them, and reduce noise and other distortions [13]. In recent years, there has been growing interest in exploring and utilizing marine resources [12], leading to a surge in research activity focused on underwater image processing and analysis [14] [15]. The marine environment poses unique challenges compared to typical image processing scenarios, such as underwater turbulence and diffusion, significant absorption and scattering of light by the water, various types of noise, low contrast, illumination, and underwater grounds [15]. In the sub-section of this, we discussed the three most impactful underwater image processing techniques from Fig. 1 UIP frameworks.

A. *Image Restoration*

Underwater image restoration aims to recover degraded images caused by various unconditional factors that are faced by AUVs in the complex underwater environment, such as camera and object motion, spectral absorption and attenuation, distortion, turbulence, optical imaging mechanisms of underwater scattering, etc [15]. Because water absorbs and scatters light differently than air, underwater picture restoration is critical because of poor image quality results. This can make it difficult for academics, oceanographers, and vision engineers to analyze and extract relevant information from underwater photographs. Underwater image restoration approaches attempt to improve underwater picture visibility and clarity by adjusting for the effects of water absorption, scattering, and turbulence. First, we will see the broad view of existing methods and their pros and cons through Table I.

TABLE I
COMPARISON OF DIFFERENT UNDERWATER IMAGE RESTORATION METHODS

Method	Advantages	Limitations
Light Propagation Physical Model [16]	Efficient in restoring details	Contains several parameters
Turbulent Degradation Transfer Factors [17]	Improves output quality	Relies on estimating transfer factors
Biologically Inspired Image-Restoration [18]	Enhances image quality	May not be suitable for all scenarios
Joint Reconstruction of Depth and Reflectivity [34]	Efficient strategy to enhance image quality	Requires accurate estimation of depth and reflectivity
Weight Graphs for Underwater Visibility [19]	Effective in strengthening visibility	May struggle with distinguishing areas with poor visibility
Polarimetric Imaging [20]	Can enhance visual quality	May have difficulty obtaining the true distribution of polarization
Aperture and Polarimetric Imaging [21]	Overcomes polarization-related limitations	Requires accurate calculation of radiation
Deep Neural Image-Recovery [31]	Preserves local characteristics	May require significant computing power
Underwater Medium Transmission Method [32]	Efficient in modeling characteristics of underwater imaging	May struggle with complex underwater scenes
Estimation of Global Background Light [33]	Enhances brightness and visibility	May require accurate estimation of background light
Flat Refraction Model [22]	Rebuilds underwater 3D shapes	May not be suitable for all image types or scenarios

For underwater image restoration, numerous strategies have been put forth, but we will explore the major advancement methods which revolutionized the restoration techniques.

In papers [16] [17], authors presented physical model-based methodologies that employ a mathematical model to evaluate the influence of turbulence on the backward scattering field. These strategies strive to limit the attenuation and degradation of the backward scattering field by computing turbulent degradation transfer factors during picture recovery and reconstruction. These strategies seek to increase the quality of underwater images by correcting for the distortions caused by turbulence in the water. In paper [18], the author was biologically inspired for improving the quality of underwater images. The method is based on the idea that human vision can distinguish the depth and reflectivity of objects in an underwater scene. By jointly reconstructing the depth and reflectivity of underwater scenes, the method seeks to improve the quality of underwater images. This technique is inspired by how the human brain processes visual information to perceive depth and reflectivity. To increase underwater visibility, the author in paper [19] created a weight graph-based approach for locating poor visibility locations. The procedure requires building a weighted network, where the vertices represent the image pixels and the edges represent how similar the pixels appear visually. By highlighting areas with low visibility and giving them more weight, the method effectively increases underwater visibility.

In papers [20] [21], authors proposed polarimetric imaging-based methods, which assess back-scatter intensity at various spatial places and compute the radiation of underwater objects by combining aperture and polarimetric imaging. This method overcomes the drawbacks of conventional polarimetric photography, which may struggle to capture the real distribution of polarisation in complex underwater scene.

In paper [22], the author presented a 3D reconstruction-based method for underwater optical imaging that utilises a flat refraction model. By reconstructing the 3D forms of underwater objects using a flat refraction model, this method seeks to fix the distortion in underwater 3D reconstruction. This approach is predicated on the notion that light rays are bent as they travel through water, distorting the three-dimensional (3D) form of underwater objects. By correcting for this distortion, the method can improve the accuracy of underwater 3D reconstruction.

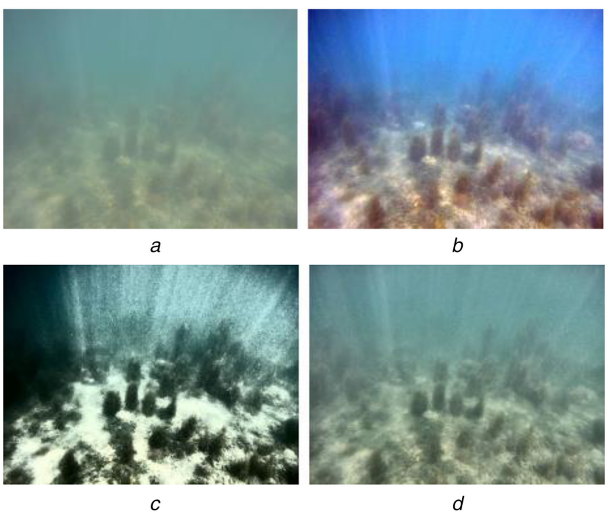

Fig. 2. [22] Figure shows the Restoration Process Results

B. Image Noise reduction

The underwater image-capturing and transmitting processes are susceptible to various noises caused by camera/sensor equipment and severe underwater environments. Poor illumination quality, optical wavelength scattering/absorption, and high-water turbidity further complicate the noise of underwater images, making noise reduction a crucial aspect of underwater image processing. In the past few decades, many noise reduction models have been explored to improve the visual appearance of underwater images and minimize background noise [15]. We will explore the most dominant and prominent approaches for noise reduction, the short overview of these methods is depicted in Table II.

TABLE II
UNDERWATER IMAGE NOISE REDUCTION METHODS

Method	Description	Advantages
Mosaicing procedure [24]	Captures small texture details	Time smoothing prior in motion parameters to reduce noise
Prime refraction rectification [25]	Reduces noise and eliminates distortions	Effective for specific types of noise
Combinational model [26]	Uses cosine similarity to tackle water turbidity	Effective for specific types of noise
Separating non-refraction sets [27]	Reduces adverse effects of refraction in underwater images	Effective for refraction-related noise
Self-similarity framework [28]	Uses super-resolution algorithm to dispel noise in high turbidity images	Effective for high turbidity images
Depth-pixel network framework [29]	Rapid enhancement algorithm using skip connections	Effective for enhancing visual details

In paper [24], the author proposed a mosaicing method for underwater videos that uses time smoothing before motion parameters to eliminate noise and distortions in the acquired underwater image. The method captures small texture details and is effective in reducing noise. The mosaicing method for underwater imaging involves capturing a sequence of overlapping images of the same scene or object, and then aligning and blending them to form a single high-quality image. This is done by first estimating the motion parameters between each pair of consecutive images, and then using these parameters to align the images. The aligned images are then blended to form a seamless mosaic. One of the challenges in mosaicing underwater images is the presence of motion and distortion caused by water turbulence. To address this, some mosaicing methods incorporate time smoothing before motion parameters, which helps to reduce noise and improve the quality of the final mosaic.

The author presented a primary refraction rectification model capable of successfully decreasing noise and correcting distortions in underwater picture capture in paper [25]. The approach is very useful for certain forms of noise.

In paper [26], the author devised a combinational model to handle the issue of water turbidity and to reduce the influence of absorption and scattering on underwater photographs. The approach addresses water turbidity using cosine similarity and is effective for certain forms of noise. To reduce the detrimental impacts of refraction in underwater photographs, the author of this work [27] presented a model that separates non-refraction sets. The approach works well for refraction-related noise.

In Paper [28], the author created a super-resolution method for underwater noise reduction and super-resolution. The approach comprises removing noise from high-turbidity underwater photos using a self-similarity framework, which employs a super-resolution algorithm to remove noise from high-turbidity images.

The depth-pixel network framework was utilized in paper [29] to create a speedy underwater picture improvement technique that leverages the skip connection to maintain visual features during the process. The procedure is good for increasing visual details and is especially beneficial for low-visibility underwater photos.

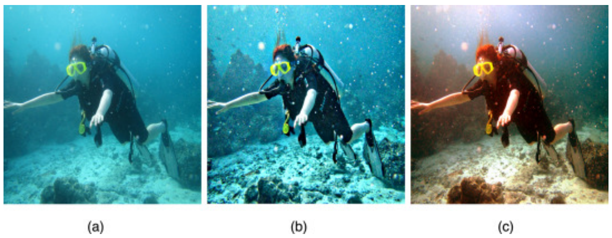

Fig. 3. [29] Figure shows the Results of Noise Reduction

C. Image Optimization

The objective of enhancing underwater images is to improve their visual appeal and make them suitable for specific applications. The primary goal is to enhance the visual attributes of the original underwater images, highlighting specific image characteristics that are relevant to the intended use. This can involve enhancing the clarity of images that are blurred due to water turbidity or emphasizing the features of a particular object in a low-light underwater environment, which may be necessary for certain analytical purposes [15]. There are numerous image optimization and enhancement techniques that are depicted exclusively in Table III. But we will explore the most dominant techniques in this domain.

A range of image enhancement techniques have been used to increase the visibility and clarity of underwater photos. The author employs an adversarial deep network-based method in paper [35] that represents picture augmentation as a distortion process.

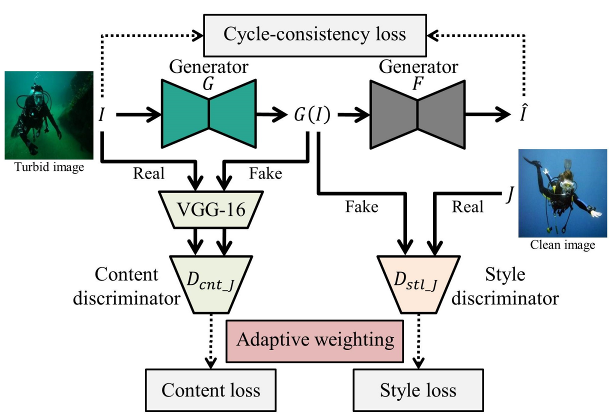

Fig. 4. [35] Adversarial Network Architecture

By minimizing a loss function that assesses the difference between the two pictures, a deep neural network is trained to learn the underlying mapping function between the original underwater image and its augmented counterpart. The network is made up of a generator that develops the ability to change

TABLE III
COMPARISON OF DIFFERENT UNDERWATER IMAGE ENHANCEMENT METHODS

Method	Advantages	Limitations
Adversarial Deep Networks [35]	Reliability, distortion-based approach	Requires large amounts of training data
Color Constancy-Based Scheme [37]	Real-time enhancement, bilateral/trilateral filters	May not work well under certain lighting conditions
Improved Retinal Algorithm with Neural Network [38]	Improved reconstruction of object edges and texture details	May introduce artifacts in the image
Color Transfer Theory and Pulse-Coupled Neural Network [41]	Simultaneous enhancement of darker regions and contrastive effect	May over-saturate colors in the image
Correction Strategies and Neural Network [42]	Focus on color distortion problem improved reflectivity and illumination	May introduce noise in the image
Guided Triangular Bilateral Filter Enhancement Model [42]	Automatic color enhancement, noise reduction, exposure of dark areas	May result in loss of image details
Local Adaptive Filtering [44]	Holistic enhancement while maintaining local characteristics	May produce unnatural colors in the image
Maximum Information-Retention Mechanism [45]	Highlighting shadows and brightness, restoring intrinsic visibility	May result in overexposed images
Adaptive Light Color Channel and Denoising Method [46]	Clearer visual appearance, noise reduction	May introduce blur in the image
Restoration Enhancement Approach [41]	Reduction of blurring effects, enhanced color and brightness	May result in loss of image sharpness
Underwater Image Enhancement Network [40]	Reliable enhancement network, the benchmark for development	Requires powerful hardware for real-time processing

an image from its input to its output and a discriminator that develops the ability to differentiate between an image that has been improved and an image that has not. The discriminator is trained to properly discriminate between the two types of pictures, while the generator is trained to trick the discriminator by producing augmented images that seem similar to the ground truth images, Process is shown in Fig.4. This adversarial training process allows the network to learn to enhance the underwater image by minimizing distortion and producing visually appealing results. One of the advantages of this approach is its reliability in producing high-quality enhancements, but it requires a large amount of training data to produce high-quality results.

In paper [37], authors developed a real-time underwater image improvement method using a colour constancy-based architecture that extends the retinex framework and includes bilateral and trilateral filters for enhancement. The technique aims to improve the visibility and clarity of underwater images by adjusting for the colour distortion and poor contrast caused by underwater photography settings. By incorporating a neural network into the retinex algorithm, the author of paper [38] improved the texture and edges of objects in underwater photographs. A data-driven neural network and a multi-scale decomposition approach are used in the strategy to overcome underwater image issues such inadequate contrast and colour distortion. These techniques provide potential ways to enhance and improve underwater image quality.

Fig. 5. [38] Retina Net Processing Result

In paper [40], the author suggested the development of a network for improving underwater images dubbed Water-Net, which they claimed could consistently improve the visibility of underwater images. In order to evaluate how well various image improvement methods work on underwater photographs, they also recommended developing a baseline for underwater image enhancement. This benchmark was intended to provide a standard evaluation platform for researchers to compare their algorithms and accelerate the development of underwater image enhancement techniques. In the paper [41], the author proposed an image enhancement model for enhancing the contrastive effect based on color transfer theory and pulse-coupled neural network. The model is designed to transfer the color statistics from a source image to the target image and generate enhanced images with improved contrast. On the other hand, In paper [42], the author focused on correcting the color distortion problem in underwater images using correction techniques. They used a neural network to generate enhanced images with improved reflectivity and illumination by training the network on a data set of underwater images. The network can be used to automatically enhance underwater images by removing color distortions.

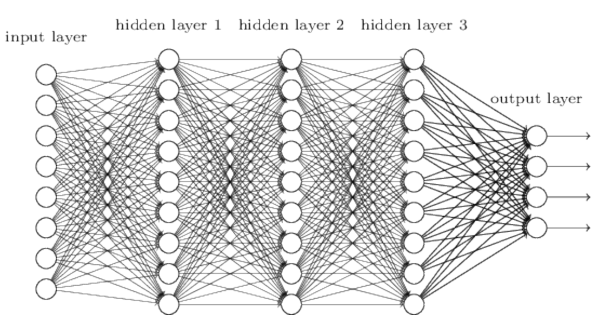

Fig. 6. [42] Artificial Neural network Architecture

D. *Motion Control*

Visual measurement and control, as previously stated, consists of two parts: Visual measurement, which is the collection of visual data (such as an object's position and pose) via sensors, is followed by visual control, which is the direction of its motion. In essence, visual feedback is utilized to control the mobility of underwater robots. Position-based servo control, image-based servo control, and mixed-servo control are the three main techniques used to regulate motion.

To accurately determine the position and pose of the object while using position-based servo control, the camera must be calibrated. Camera calibration involves determining the intrinsic and extrinsic camera parameters and once the camera is calibrated we can determine the position and pose of the object in the image. We then use a feedback control system to compare the object's actual position to its desired position using visual feedback.

Contrarily, in image-based servo control, a feedback loop is used to compare the current image with the feedback image captured by the camera to regulate the object's motion. This approach has an edge over others since it is more accurate and moves more steadily. However, obtaining a Jacobian matrix requires complex calculations that required more time complexities.

However, the third method takes into account both position and image using a feedback mechanism to regulate the object's motion. In this method, the camera is calibrated initially, and then location and pose estimation are derived from the images. This approach offers superior control performance compared to either [7].

III. Development Prospects

Despite the challenges imposed by the various aquatic conditions, visual measurement and control for underwater robotics remain a topic of intense discussion. New trends and advances in a wide range of applications are expected as a result of fast developments in hardware and software techniques. In this section, we will explore new trends in vision-based underwater robotics.

A. *Advancements in Hardware Techniques*

In the case of underwater robots, there is a potential need for hardware robustness, and a better technique is always desired. To obtain information about underwater objects, we employ sensors such as sonar and cameras. Cameras have a greater recognition degree than sonar, but analyzing the entire data set requires more processing complexity [48]. Field Programmable Gate Arrays (FPGAs) are programmable microcontrollers that are used currently in sensors hardware techniques. FPGAs are a distinct type of hardware with re-programmable gate arrays. FPGAs are being used more often in new sensor-related application areas as a result of their increasing capabilities, low cost, and potential for enhanced sensor system performance using specialized hardware technologies [47]. FPGAs provide benefits like high-speed communication interfaces, quick digital signal processing, and increased levels of parallelism. In paper [48] they used an FPGA-based image recognition system based on Convolutional Neural Network (CNN) (Convolutional Neural Network (CNN) is a mature, fast image classification algorithm [49]) for underwater robots due to their unique characteristics such as low power consumption, strong computing capability, and high flexibility. Underwater robots using such advanced methods would meet the criteria for real-time performance and durability for underwater vision.

B. Image Processing Techniques

Since handling low-quality and low-resolution images is challenging for underwater robots, advancement in the image-processing stage of computer vision through the employment of innovative technologies may be required. An innovative FPGA/DSP-based parallel architecture for real-time image processing was presented in [51] due to its high degree of parallel processing capacity. In [52], a different method for the hardware implementation of the digital image skeletonization technique using FPGA has been suggested. As additional filtering algorithms, the Extended Kalman Filter (EKF) [53] or Particle Filter has been suggested in the paper [7].

C. Embedded Vision in Bionic Underwater Robots

The usage of visual measurement and control for underwater robots have been divided into two groups based on different types of processors: embedded systems and onboard PC systems. The onboard PC system, which can handle a wide range of conditions and conforms to complex image processing algorithm requirements, is the primary system utilized in underwater robots. However, there are drawbacks attached to this as well including high volume, high energy consumption, and limited flexibility. On the other hand, the embedded system leverages its small size, low energy consumption, and tremendous adaptability to play a significant role in the field of bionics. However, the embedded system is unable to handle algorithms of high complexity due to the limits of the processors.

The limited application of complex algorithms is, however, explained by microcontroller capabilities. However, underwater robots' embedded visual systems are still in their infancy. The embedded vision-based bionic robots in aquatic settings are very advantageous due to their small size, high adaptability, and low prices [7].

Using advanced techniques for high-quality and high-resolution images, cameras can now record detailed images underwater. Similarly, using an FPGA or DSP-based visual control system in an underwater robot increased computing speed while decreasing power consumption. This has influenced its widespread application in sectors such as deep-sea exploration, submarine detection, environmental monitoring, and others.

IV. Conclusion and Future Direction

This survey focuses on the key challenges that visual techniques in aquatic environments face in underwater robots, such as fluctuating lighting conditions, non-uniformity of light beams, confounding noise from particles, limited communication between underwater vehicles and surveillance systems, and limited energy and processing resources. This study shows a state-of-the-art vision and control pipeline that includes image restoration, image noise reduction, image optimization, and motion control, as well as methodologies and techniques employed, with advantages and limitations compared. Furthermore, the development prospects, as well as new trends and innovations, have been thoroughly explored. It is widely known that vision and control are among the most difficult challenges, yet the area is expanding quickly because of advances in hardware and image processing techniques.

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