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EVOLVING TRENDS AND TECHNOLOGIES IN UNDERWATER IMAGE QUALITY IMPROVEMENT

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Abstract: Underwater image quality is enhanced through processing techniques aimed at improving both the visual clarity and overall usability of the data. Underwater computer vision related tasks rely on images that often suffer from poor contrast, low semantic visibility and color casting due to the challenging aquatic environmental conditions. Enhancing underwater visibility is essential for advancing fields such as marine science, archaeology, and autonomous underwater exploration, as it provides a clearer and more reliable basis for both human interpretation and machine-based analysis. This paper briefly discusses the significance, evolving trends and the relevant literature related to underwater image enhancement and restoration. The central idea behind this is to give readers a clear understanding of the techniques employed in the field and the current state of progress. Review concludes by highlighting the prevailing issues identified through the in-depth analysis of existing literature, suggesting possibilities for future research.

Keywords: underwater imagery, quality improvement, computer vision, pre-processing, scattering, absorption

I. INTRODUCTION

Underwater world is a vital source of resources essential for both human life and the health of our planet's ecosystem. Recently, researchers have primarily focused on analyzing and processing underwater imagery to support a wide range of real-world applications. These applications are diverse, encompassing everything from the installation of pipelines and the discovery of natural reserves to the maintenance of coral reefs, navigation of submarines, protection of marine habitats, etc. Growing need has spurred significant interest in underwater computer vision [1]. This requires computer-based systems to acquire, analyze and interpret information from digital images and videos captured in aquatic environments [2]. The central idea is to automate human visualization-based tasks using computer-aided theories and algorithms, enabling more efficient and accurate ocean exploration and management. Whenever there is a situation of working in underwater dynamic domain, new set of challenges emerge in front of researchers. Figure 1 below depicts the different types of challenges present in the underwater environment.

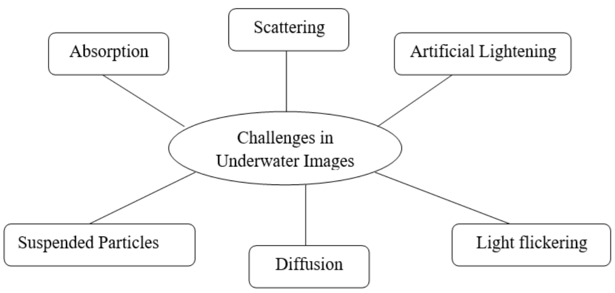

Fig. 1: Issues in Underwater Imaging

When light travels through water, it is attenuated in exponential manner and brightness of image is reduced. Light undergoes selective absorption i.e. red color is absorbed at faster rate (due to longer wavelength) in comparison to green and blue colors having shorter wavelengths. This leads to blue-green domination and color distortion in underwater images [3]. Scattering, due to suspended floating particles, poses another major challenge by modifying the direction in which light has to propagate. Forward scattering on one side, results in blurriness of image whereas, backward scattering gives rise to fogginess, lowered contrast and noise [4]. Artificial lighting tends to expand the range of visibility but on the same time, induces non-uniform illumination [5]. These issues must be taken into account whenever any of the underwater computer vision tasks needs to be accomplished.

Through pre-processing, low quality underwater images can be enhanced into clearer, higher-quality outputs. Image restoration reconstructs a damaged image using the physical model of degradation process and the characteristics of the original scene. On the other side, image enhancement employs qualitative perceptual criterion to produce a more visually acceptable image [6].

This paper presents an overview of various techniques developed to enhance the visibility of underwater images. It examines the core challenges, showcases recent advancements and based on the thorough review of existing literature, highlights the current state of the field while identifying the key directions for future innovation.

II. DEVELOPMENTS IN THE FIELD — FROM CLASSICAL TO MODERN TECHNIQUES

In response to the challenges posed by underwater imagery, researchers have proposed various techniques which are broadly categorized in this section based on their underlying methodology and approach.

Conventional techniques improve image quality by manipulating the image's histogram. These methods work by redistributing the pixel intensity values across the entire dynamic range to obtain improved resultant image in terms of color, contrast and saturation. Histogram Equalization (HE) is effective for boosting an image's overall contrast, but it falls short when specific areas need improvement. To address this, Adaptive Histogram Equalization (AHE) is introduced for local contrast improvement [7]. Instead of processing the entire image, AHE divides it into smaller regions and performs histogram equalization on each one. This method uses a pixel-to-pixel transformation, where each pixel's value is adjusted based on the histogram of its surrounding neighborhood. Since AHE operates on small, often homogeneous regions, the local histograms can have sharp and narrow peaks. This can lead to over-enhancement in certain cases, amplifying noise and creating an unnatural appearance. To counteract this, Contrast-Limited Adaptive Histogram Equalization (CLAHE) came into picture. CLAHE prevents over-enhancement by clipping the sharp peaks of the local histograms to a predefined limit [8][9]. After clipping, excess pixel values are redistributed evenly across the histogram, ensuring a more uniform distribution. This controlled method enhances local contrast and prevents noise from increasing, which results in a more natural and visually appealing image. Image fusion combines information from multiple source images to create a single, superior output image [9][10]. This process aims to produce a final image that is more comprehensive and of better quality than any of the individual inputs. A common application is multi-focus image fusion in which multiple images of the same scene are taken, each with a different part in focus [11]. Fusion algorithm then selects the sharpest regions from each image and blends them together to generate a single image where the entire scene is in focus.

Prior-based techniques rely on preliminary information about the input image before processing [12]. Prior knowledge can include details about the type of degradation, the nature of the capturing device or the environmental conditions that helps in fine-tuning the processing parameters and analyzing any unknown factors. These techniques restore a degraded image by using a physical model and a statistical prior to invert the image formation process. [13][14]. The Dark Channel Prior (DCP) is among the most widely adopted prior-based methods for restoring underwater image quality [12]. It operates on the basis of observation that for any given local patch in haze-free outdoor image, at least one of the color channels from Red, Green or Blue will contain some pixels with very low intensity values. To remove haze, DCP algorithm first estimates the atmospheric light, then refines a transmission map to accurately model the haze's effect on each pixel, and finally, uses this refined information to recover the original, haze-free image [14]. For the oceanic environment, a modified version of DCP known as the Red Channel Prior developed [15]. This adaptation stems from the fact that red color is rapidly absorbed in water, resulting in the lowest intensity values regardless of the type or degree of distortion.

Deep learning-based approaches learn to correct degraded images by analyzing large datasets, rather than using physical models of light behavior in water. This strategy allows them to learn complex features and transformations needed to improve an image's quality. Two main types of networks used are Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) [16][17]. CNNs are trained on the paired datasets containing degraded images and corresponding good quality image referred as ground truth. Concept is based on an image-to-image translation in which network figures out the mapping between input degraded image and output clear image on its own. Generative Adversarial Networks (GANs) are being applied to generate synthetic databases for real-time underwater image processing. GANs are based on two networks: one is generator and the other is discriminator [18]. Generator generates the enhanced versions of degraded underwater images, while the discriminator's role is to distinguish between real, high-quality images and the synthetic ones produced by the generator [19]. Generator's objective is to create images so convincing that the discriminator cannot tell them apart from real ones, while the discriminator aims to correctly identify the synthetic images. This adversarial process pushes the generator to continually improve the image quality, enhancing contrast, color and overall visibility.

III. LITERATURE ANALYSIS

Several papers have been surveyed to analyze the existing literature, focusing on key considerations, techniques, trends and technologies — both traditional and state-of-the-art. This section briefly discusses a few of them.

Ma et al. [9] proposed CLAHE based technique relying upon fusion of two distinct color spaces: HSI (components are hue, saturation, intensity) and YIQ (components are luminance, hue, saturation). RGB image is initially converted into HSI as well as YIQ color space. To obtain the enhanced version of luminance component in YIQ and intensity component in HSI space, CLAHE algorithm is applied on both of these. Improved HSI and YIQ spaces are shifted back to RGB color space (enhanced versions referred as HSI-RGB and YIQ-RGB). To address non-coherency of three respective components (red, green and blue) in HSI-RGB/YIQ-RGB images, color harmonization is carried out. HSI-RGB and YIQ-RGB images are unified with the help of Euclidean norm and fused image is further enhanced by applying General Log Ratio (GLR) multiply operation with 4 directional Sobel edge detector. Metrics to analyze the technique are contrast, mean, entropy, Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR) and colorfulness.

Hou et al. [20] proposed a hybrid approach for underwater image enhancement that integrates both HSI and HSV (components are hue, saturation, value) color spaces to maintain hue fidelity. The method begins by converting the original RGB image into the HSI domain, where wavelet-domain filtering is applied to the Saturation and Intensity channels, leaving the Hue channel untouched. The image is then transformed into the HSV color model, where constrained histogram stretching is performed on the Saturation and Value channels, again preserving the Hue component. Although the technique was not evaluated on ideal reference images, it is computationally efficient and outperforms existing methods in terms of discrete entropy, contrast and PSNR. Additionally, it enhances color accuracy and mitigates issues related to non-uniform illumination.

Yang et al. [21] proposed a model for underwater image processing based on hybrid of feature normalization with recurring neural networks. For performance improvement, multiple activation maps are applied. Size of the various filters (kernels) which are used at each activation layer for feature transformation is determined based on the difference in attenuation levels of various color channels. Feature map at each layer is feed-forwarded to the subsequent layer in the network. Parameters deployed for evaluation of the technique are Structural Similarity Index (SSIM), PSNR. Datasets used for performance testing are UFO-120 [22] and EUVP [23] underwater imaging datasets. Technique performs well for depth estimation and computer vision related tasks. However, model is still required to be tested for complex applications like image dehazing.

Gao et al. [24] proposed a technique for underwater image contrast enhancement based on multiple perspective fusion. Firstly, the image is reconstructed using red channel prior. Basically, the idea is to compensate that color channel with higher levels of distortion. Red color due to longer wavelength attenuates faster so, the details are nearly lost. Depth estimation maps are generated with respect to each color channel to estimate the amount of light actually reaching the object without being scattered. Now, transformation (or restoration) is done for the channel containing pixels with lowest intensity levels. Here, two different variants are obtained for the transformed image from previous step. For first, local contrast enhancement is done for refinement of edges and other fine details. Laplacian (contrast) weight is evaluated to assure that edges possess high intensity values. Saliency and gradient weights are added in order to highlight edges and determine the region of interest (ROI). Image pixel based gradient weights are calculated using gradient magnitudes. Another version is obtained by post-processing with unsharp filtering or blurring. Both the variants now combined using multiple scale fusion. Technique cannot eliminate speckle (due to light scattering) noise. Also, it still has to deal with such images that possess blurriness due to motion.

Liu and Liang [25] implemented another technique for underwater imaging refinement on the basis of attenuation slope. Prior information is generated based on the statistical inferences from this attenuation slope. Further, transformations are carried out based on the prior. For this, the color pixel values are represented in RGB color space followed by their distribution on the attenuation slope based on the varying attenuation values in changing underwater conditions. Color channel casting is applied for initial processing and to calculate the attenuation difference. The technique uses the reverse mapping to evaluate the ground truth i.e. for computation of the areas in the input image with attenuation distortion. White balancing and guided image filtering is used for final processing. White balancing ensures that white color in the resultant image renders actual white, not some other color. Guided filter preserves the image characteristics i.e. edges, texture etc. Evaluation parameters are SSIM, PSNR and Level of Enhancement (LOE). Technique works for noise filtering, color correction and prevents over-enhancement.

Priyadharshini et al. [26] proposed a methodology in which distorted raw image undergoes white balancing to deal with color cast, gamma correction to adjust the brightness and CLAHE to improve the contrast. Pre-processed images are resized and concatenated for giving as an input to primary convolutional neural network block. In parallel, separate feature transformation blocks process the raw image and a pre-processed version of it using multiple convolutional layers and activation functions. Final enhanced image is generated by multiplying and merging the outputs from the main CNN and the Feature Transformation blocks. Performance analysis is done both quantitatively and qualitatively. Metrics for quantitative analysis are MSE, PSNR, SSIM. Authors intend to evaluate the technique's potential for diverse underwater imaging applications in future.

Saleh et al. [27] has worked on an unsupervised network which addresses the issue of uncertainties arising from different ambiguous scenarios, where different images may require varying degrees of processing. Learning based model Uncertainty distribution (UDNet) network is introduced to integrate this uncertainty to the proposed model's training process. It aims to provide the series of enhancement results, rather than a single correct result, as sometimes it is not possible to produce a reference/ground or unaltered image. As it is a probabilistic approach, a module i.e. multicolor space stretch assist inducing randomness, generating reference maps by either applying contrast, saturation improvement or gamma correction, followed by color-based stretching. Subsequently, generated feature maps are further fed to the conditional variational encoder (CVaE) mechanism to generate the feature rich image by encoding the predicted uncertainties. Concurrently, adaptive instance normalization (PAdaIN) is used for mapping the differences in color and textures based on image batches. Performance of the proposed method is evaluated for several paired and unpaired datasets using performance parameters such as PSNR, SSIM, MAD etc.

Du et al. [28] introduces a novel framework, UIEDP, to significantly improve underwater image quality. Instead of relying on poor-quality synthetic data for training, method reframes enhancement as a conditional generative task. It cleverly combines a pre-trained diffusion model, which has a strong understanding of natural image aesthetics, with an existing enhancement algorithm. Output of the initial algorithm acts as a guide, or pseudo-label, for the diffusion model, resulting in final images that are both visually natural and measurably superior to those produced by traditional methods. This adaptable framework can boost the performance of existing underwater image enhancement techniques. Evaluation metrics used are PSNR, SSIM, Underwater Image Quality Measure (UIQM), Naturalness Image Quality Evaluator (NIQE), etc.

Mishra et al. [29] proposed a technique which initiates with applying white balancing to the input image to remove the undesirable casts while pre-processing. Following, the color image is transformed to the YC_bC_r format to extract the reflectance and illumination parts from the luma component. A Retinex algorithm is utilized for the aforementioned purpose and thereafter, both the parts are separately processed for color, brightness improvement using techniques such as weighted histogram, Gaussian, probability density function etc. Eventually, the various elements of YC_bC_r are concatenated together and transformed back to RGB color space for the resultant image. Evaluation is carried out on standard underwater image dataset using non-reference quality parameters. Future research will focus on two key areas: mitigating the bluish cast in enhanced images and restoring scenes captured under lesser illumination.

Fayaz et al. [30] developed a dual-path underwater image restoration method. It restores a hazy image using two different approaches simultaneously. First uses a Dark Channel Prior derived from a contrast code picture, and the second uses a Bright Channel Prior from the luminance component of the YC_rC_b color space. After the initial restoration, each of the output is enhanced: dark channel result is sharpened, while the bright channel result undergoes gamma correction to control brightness. Two enhanced images are then intelligently fused together, guided by three separate weight maps i.e. saliency, Laplacian contrast and saturation to combine the best features of each image at a pixel level. Performance is measured using objective metrics like Entropy, NIQE and Underwater Image Sharpness Measure (UISM).

IV. PREVAILING ISSUES

A key challenge in underwater image processing is the severe degradation of image quality caused by the aquatic environment. Water and suspended particles absorb and scatter light, resulting in substantial loss of color fidelity, contrast and fine details [4][31]. This degradation appears as prominent color casts, reduced visibility and a hazy appearance which pose obstacles to both human interpretation and automated image analysis [32]. Another problem is the lack of generalizability across diverse underwater environments [6].

For instance, a method developed for visibility enhancement in a shallow-water setting may prove ineffective when applied to the different light attenuation and scattering properties of a deep-sea environment [33]. To validate the efficacy of the proposed method, it is desirable to conduct a comprehensive performance evaluation within the context of aquatic computer vision tasks, including object classification and detection [26][33]. Algorithms developed must be effective for real-world scenarios, particularly for use in autonomous underwater vehicles (AUVs) and other underwater robotic systems [21].

V. CONCLUSION

Processing underwater images is essential for computer vision tasks but is highly challenging due to issues like color distortion, uneven contrast and light scattering. The processing needs are dynamic and changing with each unique scenario. Although image processing techniques have advanced over time to meet evolving application needs, current models still produce apparent results in some cases which require further validation. Supervised methods face a shortage of paired datasets due to the difficulty of capturing clear images at great depths, while unsupervised methods may struggle to adapt to real-world underwater conditions due to limited size of synthetic data. Hybrid approaches that combine traditional and modern techniques have shown promising results at times with limited data and greater depths, but these methods can even introduce complexity and necessitate extensive fine-tuning for different components. All this highlights the need for more efficient, adaptable solutions capable of handling the diverse and dynamic conditions of underwater environments.

VI. REFERENCES

[1] P. Naveen, "Advancements in underwater imaging through machine learning: Techniques, challenges, and applications," *Multimedia Tools Appl.*, pp. 1-20, 2024.

[2] M. Salhaoui, J. C. Molina-Molina, A. Guerrero-Gonzalez, M. Arioua, and F. J. Ortiz, "Autonomous underwater monitoring system for detecting life on the seabed by means of computer vision cloud services," *Remote Sens.*, vol. 12, no. 12, Art. No. 1981, 2020.

[3] S.-C. Pei and C.-Y. Chen, "Underwater images enhancement by revised underwater images formation model," *IEEE Access*, vol. 10, pp. 108817-108831, 2022.

[4] J. Zhou, S. Chen, D. Zhang, Z. He, K.-M. Lam, F. Sohel, and G. Vivone, "Adaptive variational decomposition for water-related optical image enhancement," *ISPRS J. Photogramm. Remote Sens.*, vol. 216, pp. 15–31, 2024.

[5] J. Ma, M. Wang, G. Hou, W. Zhang, and B. Huang, "PQGAL-net: Perceptual quality guided generative adversarial learning for non-uniform illumination underwater image enhancement," *Digit. Signal Process.*, vol. 160, Art. No. 105048, 2025.

[6] N. Deluxni, P. Sudhakaran, and M. F. Ndiaye, "A review on image enhancement and restoration techniques for underwater optical imaging applications," *IEEE Access*, vol. 11, pp. 111715-111737, 2023.

[7] S. Jin, P. Qu, Y. Zheng, W. Zhao, and W. Zhang, "Color correction and local contrast enhancement for underwater image enhancement," *IEEE Access*, vol. 10, pp. 119193-119205, 2022.

[8] Y. Chang, C. Jung, P. Ke, H. Song, and J. Hwang, "Automatic contrast-limited adaptive histogram equalization with dual gamma correction," *IEEE Access*, vol. 6, pp. 11782–11792, 2018.

[9] J. Ma, X. Fan, S. X. Yang, X. Zhang, and X. Zhu, "Contrast limited adaptive histogram equalization-based fusion in YIQ and HIS color spaces for underwater image enhancement," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 32, no. 07, pp. 1–26, 2018.

[10] C. O. Ancuti, C. Ancuti, C. De Vleeschouwer, and P. Bekaert, "Color balance and fusion for underwater image enhancement," *IEEE Trans. Image Process.*, vol. 27, no. 1, pp. 379–393, 2017.

[11] Y. Zhou *et al.*, "A survey of multi-focus image fusion methods," Appl. Sci., vol. 12, no. 12, Art. No. 6281, 2022.

[12] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, 2010.

[13] Z. Liang, W. Zhang, R. Ruan, P. Zhuang, X. Xie, and C. Li, "Underwater image quality improvement via color, detail, and contrast restoration," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 34, no. 3, pp. 1726–1742, 2023.

[14] C. Li, J. Guo, C. Guo, R. Cong, and J. Gong, "A hybrid method for underwater image correction," *Pattern Recognit. Lett.*, vol. 94, pp. 62–67, 2017.

[15] A. Galdran, D. Pardo, A. Picón, and A. Alvarez-Gila, "Automatic red-channel underwater image restoration," *J. Vis. Commun. Image Represent.*, vol. 26, pp. 132–145, 2015.

[16] S. Anwar and C. Li, "Diving deeper into underwater image enhancement: A survey," *Signal Process. Image Commun.*, vol. 89, Art. No. 115978, 2020.

[17] A. Menon and R. Aarthi, "A hybrid approach for underwater image enhancement using cnn and gan," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 6, 2023.

[18] K. K. Babu, A. Tabassum, B. Navaneeth, T. Jahnavi, and Y. Akshaya, "Underwater image enhancement using generative adversarial networks: a survey," *Int. J. Comput. Appl.*, vol. 47, no. 4, pp. 356–372, 2025.

[19] Y. Guo, H. Li, and P. Zhuang, "Underwater image enhancement using a multiscale dense generative adversarial network," *IEEE J. Ocean. Eng.*, vol. 45, no. 3, pp. 862–870, 2019.

[20] Hou, G., Pan, Z., Huang, B., Wang, G., & Luan, X. (2018). Hue preserving-based approach for underwater colour image enhancement. *IET Image Process.*, *12*(2), 292-298.

[21] H.-H. Yang, K.-C. Huang, and W.-T. Chen, "LAFFNet: A Lightweight Adaptive Feature Fusion Network for Underwater Image Enhancement," in *2021 IEEE Int. Conf. Robot. Autom. (ICRA)*, Xi'an, China, pp. 685-692, 2021.

[22] M. J. Islam, P. Luo, and J. Sattar, "Simultaneous Enhancement and Super-Resolution of Underwater Imagery for Improved Visual Perception," *arXiv preprint arXiv:2002.01155*, 2020.

[23] M. J. Islam, Y. Xia, and J. Sattar, "Fast Underwater Image Enhancement for Improved Visual Perception," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 3227-3234, Apr. 2020.

[24] F. Gao, K. Wang, Z. Yang, Y. Wang, and Q. Zhang, "Underwater Image Enhancement Based on Local Contrast Correction and Multi-Scale Fusion," *J. Mar. Sci. Eng.*, vol. 9, no. 2, pp. 1-16, Feb. 2021.

[25] K. Liu, and Y. Liang, "Underwater image enhancement method based on adaptive attenuation-curve prior," *Opt. Express*, vol. 29, no. 7, pp. 10321-10345, Mar. 2021.

[26] R. A. Priyadharshini, S. Arivazhagan, K. A. Pavithra and S. Sowmya, “An ensemble deep learning approach for underwater image enhancement,” *e-Prime-Adv. Electr. Eng. Electron. Energy*, vol. 9, Art. No. 100634, 2024.

[27] A. Saleh, M. Sheaves, D. Jerry, and M. R. Azghadi, “Adaptive deep learning framework for robust unsupervised underwater image enhancement,” *Expert Syst. Appl.*, vol. 268, Art. No. 126314, 2025.

[28] D. Du, E. Li, L. Si, W. Zhai, F. Xu, J. Niu, and F. Sun, “UIEDP: Boosting underwater image enhancement with diffusion prior,” *Expert Syst. Appl.*, vol. 259, Art. No. 125271, 2025.

[29] A. K. Mishra, M. S. Choudhry, and M. Kumar, "Underwater image restoration using white balance and retinex algorithm," in *2022 IEEE Conf. Interdiscipl. Approaches Technol. Manage. Social Innov.*, 2022, pp. 1–5.

[30] S. Fayaz, S. Parah, and G. J. Qureshi, “Subd: Single Underwater Image Dehazing Using Bright and Dark Channel Information with Contrast Coding,” SSRN, 2023.

[31] T. Wang, L. Wang, E. Zhang, Y. Ma, Y. Wang, H. Xie, and M. Zhu, "Underwater image enhancement based on optimal contrast and attenuation difference," *IEEE Access*, vol. 11, pp. 68538-68549, 2023.

[32] M. Kanagavel and V. Thanikaiselvan, "Adjustment of pixel intensity for removal of color casts in underwater images," *IEEE Access*, vol. 12, pp. 32266-32277, 2024.

[33] Y. M. Alsakar, N. A. Sakr, S. El-Sappagh, T. Abuhmed, and M. Elmogy, "Underwater image restoration and enhancement: a comprehensive review of recent trends, challenges, and applications," *Vis. Comput.*, vol. 41, no. 6, pp. 3735-3783, 2025.

