Enhancement of Underwater Video through Adaptive Fuzzy Weight Evaluation

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Abstract—**Underwater video enhancement plays a critical role in improving the visibility and quality of underwater imagery, which is essential for various applications such as marine biology, underwater archaeology, and offshore inspection. In this article, we present a novel approach for enhancing underwater videos. Our method employs fuzzy logic and a unique fuzzy channel weight coefficient to effectively address challenges in underwater imaging. The method aims to improve the perceptual quality of underwater videos by enhancing contrast, reducing noise, and increasing overall image clarity. The key component in our approach is the integration of fuzzy logic based channel weight coefficient which is adaptively selected to enhance the video frames. The fuzzy channel weight coefficient-based method assigns weights to different color channels in a manner that optimally addresses the underwater imaging conditions. To evaluate the performance of our fuzzy enhancement algorithm, we conducted experiments on the Fish4Knowledge database, a widely used benchmark dataset for underwater video analysis. We quantitatively assessed the improvement in video quality using various metrics, including Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), Structural Similarity Index (SSIM), and entropy. Our results demonstrate that the proposed fuzzy logic-based enhancement method outperforms existing techniques in terms of video quality enhancement and underwater image correction in terms of PSNR, RMSE and SSIM.**

Keywords—Underwater Video Enhancement; Adaptive Weight Assignment; Adaptive Contrast Enhancement; Fuzzy Logic; Fuzzy Interference System (FIS); Membership Function.

I. INTRODUCTION

The mysterious depths of our planet's oceans have long been a source of fascination and wonder. The vibrant, otherworldly ecosystems hidden beneath the surface hold secrets of biodiversity, geological phenomena, and potential solutions to global challenges. However, despite the advancements in technology, translating this concealed beauty into high-quality video footage remains a daunting task. Underwater video recordings are persistently challenged by factors such as poor visibility, light absorption, and color distortion, all of which can significantly compromise the clarity and comprehensibility of the captured imagery [1][2].

This article embarks on a pioneering journey to tackle these longstanding issues. It is a crucial step in bridging the gap between our curiosity about the underwater world and our ability to faithfully represent it on video. The approach proposed here harnesses the innovative concept of adaptive fuzzy weight evaluation [5] to address the multifaceted challenges inherent to underwater video enhancement.

In the subsequent sections of this article, we embark on an in-depth exploration of the complexities and imperfections plaguing underwater video capture. We delve into the theoretical underpinnings of our approach, providing a comprehensive understanding of the adaptive fuzzy weight evaluation framework. This methodology, informed by an assessment of dynamic variables such as water turbidity, ambient light conditions, and particle density, offers a sophisticated solution to enhance the clarity, contrast, and color fidelity of underwater video recordings.

By recalibrating the weights assigned to different image components based on these factors, our approach adapts to the dynamic nature of underwater environments, resulting in a marked improvement in video quality. The Proposed fuzzy based underwater video enhancement algorithm improves underwater video quality in terms of PSNR and SSIM. The proposed algorithm effectively enhances contrast of the underwater videos.

Furthermore, the practical applications of this method are not limited to a single domain [3][4][28][29][30]. The implications of our research extend to scientific endeavors, enabling marine biologists to more effectively study aquatic life, environmentalists to monitor underwater ecosystems, and security agencies to enhance surveillance in maritime environments. Additionally, the burgeoning underwater filmmaking and tourism industries stand to gain from this technological breakthrough, as it promises to deliver unprecedented visual experiences to the audience [27].

Through this article, we aim not only to enhance the quality of underwater video but also to open new vistas of exploration, understanding, and appreciation of our planet's submerged realms. In doing so, we hope to stimulate further research and innovation in the domain of underwater video enhancement and contribute to our evolving comprehension of the oceans vital role in the global ecosystem.

In this article, we present a new approach for enhancing underwater videos. Our method employs fuzzy logic and fuzzy channel weight coefficient to effectively address challenges in underwater imaging. More specifically, underwater vidoes undergoes different levels of attenuation. The equal color compensation strategy for each RGB channel is less effective. Hence, this study presents adaptive color compensation using adaptive fuzzy weight assignment. The major contributions of this work can be summarized as:

1. A new approach using fuzzy based adaptive weight computation for channel compensation is developed.
2. The proposed fuzzy weight assignment strategy attains superior performance compared with state-of-the-art methods.

This article is organized as follows: Section I provides an Introduction, through a comprehensive literature review in Section II, methodological elucidation, and empirical experimentation that has been performed by various literature has been considered, In section III presents the proposed method and its algorithm that is used in significantly improving video quality by mitigating challenges such as low visibility and color distortion, and Section IV represents highlights the utility of fuzzy logic in addressing complex environmental challenges and the results obtained have also been discussed, and finally the conclusion is summarized in last section.

II. Literature Review

The need for higher-quality footage in aquatic conditions has led to a significant increase in the field of underwater video enhancement over time. Numerous approaches have been investigated by researchers to overcome the difficulties involved in capturing underwater video. Techniques for enhancing contrast have attracted a lot of interest among them. Among the popular techniques for improving contrast and visibility in underwater videos are wavelet-based techniques [31-38], adaptive histogram stretching [39-47], and histogram equalization [41-48]. Furthermore, colour distortion brought on by water absorption and dispersion has been countered by colour correcting algorithms [56-57]. Through the restoration of natural colours, these techniques hope to improve the accuracy of marine species identification, coral reef analysis, and underwater geological feature studies.

Noise reduction is a critical component of underwater video enhancement. Noise may affect image quality and is frequently introduced during video collection. To reduce noise while maintaining crucial features, researchers have used a variety of denoising techniques, such as wavelet-based denoising, temporal filtering, and spatial filtering. Furthermore, methods for image stabilization [58-62] have been created to compensate for the motion-induced distortions that are frequently seen in underwater videos. Underwater video enhancement is poised to make significant contributions to environmental monitoring [63][64], marine biology [65], underwater archaeology [66-68], and offshore enterprises as technology and study in this field progress, expanding our understanding of the world under the waves.

Enhancing underwater video is crucial for a wide range of applications, including fisheries assessment, biodiversity monitoring, and underwater exploration. However, underwater video often suffers from poor visibility due to factors such as light attenuation, scattering, and color distortion [27]. To tackle this challenge, several methods have been proposed to enhance the visibility and quality of underwater video.

Hanmandlu et al. [5] To optimize and improve the quality of colour photographs, the strategy combines a fuzzy system with the Bacterial Foraging algorithm, a bio-inspired optimization technique. The combination of fuzzy logic and the Bacterial Foraging algorithm allows the system to process and enhance colour photos in an adaptable manner, with a focus on fixing contrast and colour balance concerns. By efficiently resolving the complexities of colour picture enhancement, this unique technique exhibits its usefulness in a variety of disciplines, including image processing, computer vision, and multimedia. The paper's main contribution is its capacity to perform colour picture enhancement while taking individual image qualities into account, a quality that makes it invaluable for accurate image processing and analysis across a wide range of technical and scientific applications.

Om Prakash Verma et al. [6] presents an advanced method for enhancing color images with high dynamic range. This innovative approach leverages the Artificial Ant Colony System to optimize and enhance color images, with a particular focus on addressing the challenges posed by images with varying levels of contrast and illumination. By combining the principles of fuzzy logic and the Artificial Ant Colony System, the authors achieve dynamic and adaptive image enhancement, offering potential applications in fields such as computer vision, remote sensing, and medical imaging.

Hasikin et al. [7] The research provides an adaptive technique that uses fuzzy intensity metrics to improve image quality. This technique is intended to dynamically modify intensity levels in response to changes in illumination, resulting in better visibility and contrast, especially in situations when typical image enhancement methods fail. The paper's contribution is its ability to address real-world problems effectively, making it useful for applications in computer vision, medical imaging, and remote sensing. The suggested technique, by adjusting to the unique image conditions, presents a viable solution to the augmentation of non-uniformly lighted and low-contrast images, thereby opening new paths for image processing and analysis in tough environments.

Sarkar et al. [8] demonstrates a novel technique to multi-level image thresholding. The method blends fuzzy entropy measures with the strong Differential Evolution optimization tool. As a result, it provides a framework for properly segmenting images into several levels based on intensity. This technique is very valuable in image analysis and processing because it allows for more exact and varied segmentation, which is important in applications such as object recognition, medical imaging, and pattern analysis. The articles contribution is its ability to adaptively establish threshold levels and improve image segmentation accuracy and efficiency in scenarios when traditional thresholding algorithms may fall short. Because of the synergy between fuzzy entropy and Differential Evolution, it is a promising technique for handling complex image segmentation challenges in a variety of domains.

Sethi et al. [9] This method combines the Fuzzy Gray World algorithm with the Bacterial Foraging algorithm to address the challenges of underwater image quality. By leveraging fuzzy logic and a bio-inspired optimization technique, the authors aim to effectively correct color distortion and enhance image contrast in underwater settings. This approach holds great promise in applications such as marine exploration, environmental monitoring, and underwater imaging. It contributes to the field of image enhancement by offering a unique combination of algorithms that adapt to the specific conditions of underwater environments, resulting in improved image quality and color accuracy. The synergy of these algorithms makes it a valuable tool for enhancing underwater imagery and addressing the complexities associated with color correction in such scenarios.

Sudhavani et al. [10] this article introduces three contrast enhancement methods utilizing fuzzy logic principles to improve the contrast of specific image features. The first technique employs straightforward fuzzy if-then rules to obtain the fuzzy system response function. In the second technique, the fuzzy contrast intensification operator is harnessed as a means of enhancement. The third technique leverages fuzzy expected values to enhance image features.

Srividhya et al. [11] This method uses fuzzy logic to denoise photos adaptively, taking into account the unique qualities and environmental conditions of underwater sceneries. By doing so, the authors efficiently minimize noise and improve image quality, making this technique particularly useful for marine research, underwater archaeology, and surveillance in difficult underwater conditions. While implementation may necessitate some technical knowledge, the paper's technique stands out for its potential to considerably increase the quality of underwater photos, therefore contributing to advances in the field of underwater image improvement.

Akila et al. [12] introduced the Enhanced Fuzzy Intensification method, which involves enhancing fuzzy membership functions for each color channel and employing fuzzy-based pixel intensification to remove haze, enhance visibility, and improve color quality. Furthermore, a post-processing step is implemented, using fuzzy histogram equalization specifically for the red channel when it exhibits the highest pixel values. The proposed method yields superior results in terms of maximum entropy and PSNR while minimizing MSE, all achieved with significantly reduced computational time compared to existing approaches.

Sarkar et al. [13] This method involves two key components: fuzzy-based contrast improvement and partition-based thresholding. By applying fuzzy logic, the authors adaptively enhance the image's contrast, addressing challenges posed by underwater conditions. Subsequently, partition-based thresholding is used to separate objects from the background. This approach is crucial for underwater image analysis, aiding in tasks like object recognition and marine research. The primary focus of this paper is its contribution, which is its innovative method for image segmentation in underwater environments. The synergy of fuzzy logic and partition-based thresholding allows for precise and effective image segmentation, a vital aspect of image analysis in various scientific and technical fields.

Chen et al. [14] introduces a unique dimension to the field by utilizing temporal intuitionistic fuzzy sets. This innovative approach involves the incorporation of intuitionistic fuzzy logic and temporal analysis to process video data. The paper showcases the potential of this method, offering applications across various domains, including video analytics, computer vision, and surveillance systems. By harnessing the capabilities of temporal intuitionistic fuzzy sets, the authors aim to address the intricacies of video data, enhancing its analysis and interpretation. The paper makes a significant contribution in its pioneering application of temporal intuitionistic fuzzy sets to video processing, which has the potential to elevate the quality and precision of video analytics and related fields, offering a new dimension to research in this domain.

Z. Wang et al. [15] introduced a Two-phase Underwater Domain Adaptation network (TUDA) that concurrently addresses both the inter-domain and intra-domain gaps. The proposed TUDA, featuring a triple-alignment network and a rank-based underwater quality assessment method, showcases significant improvements in both visual quality and quantitative metrics, providing a promising solution for enhancing underwater images across various applications.

The three components that make up the Realistic LR Image Generation Module (RLGM), Dual-Degradation Estimation Module (DEM), and Enhancement and Super-Resolution Module (ESRM) of the Realistic Underwater Image Enhancement and Super-Resolution network (RUIESR) are presented by Y. Li et al. [16] Realistic LR images are produced by RLGM, textures are improved and colour casts are corrected by ESRM, and dual-degradation priors are precisely estimated by DEM. RUIESR is a potential approach for advancing underwater image improvement and super-resolution networks, as demonstrated by extensive experiments on actual and synthetic underwater datasets, showing that it beats existing methodologies in terms of visual quality and quantitative metrics.

The Weighted Wavelet Visual Perception Fusion (WWPF) technique for efficient improvement is presented by W. Zhang et al. [17] WWPF consists of a rapid integration-optimized local contrast technique, an attenuation-map-guided colour correction, and a maximum information entropy-optimized global contrast strategy. WWPF efficiently combines high-frequency and low-frequency components at multiple scales to produce high-quality underwater images by utilising a weighted wavelet visual perception fusion method. Comprehensive tests on three benchmarks show that WWPF is superior to state-of-the-art techniques in terms of both quality and quantitative outcomes. The WWPF-processed photos also demonstrate useful advantages for applications underwater.

J. Zhou et al. [18] presented an innovative underwater image enhancement method employing multi-interval subhistogram perspective equalization. The method tackles the global nonuniform drift of feature representation by estimating feature drifts in different image areas based on statistical characteristics. This information guides adaptive feature enhancement, improving the visual effect of degraded images. The proposed approach incorporates a variational model for enhanced color correction through subinterval linear transformation, along with a multithreshold selection method for adaptive threshold array selection. The culmination of these techniques is the introduction of a multi-interval subhistogram equalization method, enhancing image contrast through histogram equalization in each subhistogram. Comprehensive experiments on various underwater scenarios demonstrate the superior qualitative and quantitative performance of the proposed method compared to state-of-the-art approaches.

J. Zhou et al. [19] delivered a comprehensive review of underwater vision enhancement technologies, addressing the challenges in achieving optimal visual quality for images captured by underwater cameras. It covers the theory of underwater image degradations, formation models, and a systematic overview of enhancement technologies proposed in recent decades. The study also highlights existing underwater image datasets and conducts extensive experiments to assess the limitations and strengths of various enhancement methods.

Y. Rao et al. [20] propose a novel probabilistic color compensation network analyzing color spectrum distribution in common underwater datasets. Instead of directly learning enhancement mapping, their approach prioritizes learning color compensation for general purposes. The two-stage enhancement framework, incorporating color compensation followed by enhancement, consistently outperforms conventional and learning-based methods across challenging scenarios. Enhanced images exhibit superior performance in underwater salient object detection and visual 3D reconstruction, overcoming generalization limitations of existing models.

J. Zhou et al. [21] outlined a cross-domain enhancement network (CVE-Net) utilizing high-efficiency feature alignment for improved utilization of cross-view neighboring features. With a self-built database optimizing relevant information and a feature alignment module (FAM) adapting temporal features, CVE-Net outperforms state-of-the-art methods in both qualitative and quantitative assessments. Achieving a PSNR of 28.28 dB, 25% higher than Ucolor on the multi-view dataset, CVE-Net successfully enhances image quality while maintaining a favorable complexity-performance trade-off.

III. PROPOSED ALGORITHM

The Proposed algorithm outlines a systematic approach for enhancing the quality of underwater videos through the application of Adaptive Fuzzy Weight Evaluation (AFWE) (see Fig. 1). It encompasses a series of intricately designed steps, commencing from pre-processing to post-processing, with the primary objective of significantly improving visibility, image clarity, and overall video quality in challenging underwater scenarios.

A. Step 1: Preprocessing

1) Loading the Underwater Video

In this initial stage, the algorithm loads the target underwater video to be subjected to the enhancement process.

2) Frame Extraction

The RGB frames are extracted from the video sequence. These frames serve as the raw material for further analysis and enhancement.

3) Conversion to Fuzzy RGB Channels

Each extracted RGB frame undergoes a conversion process, transforming it into fuzzy RGB channels. This step sets the stage for subsequent analysis based on fuzzy logic.

B. Step 2: Compute Frame Statistics

1) Mean and Standard Deviation Calculation

In this phase, the algorithm calculates the mean and standard deviation of pixel intensity values within each frame. These statistical measures are used to quantitatively assess the overall brightness and contrast of the image.

C. Step 3: Fuzzy Weight Calculation

1) Individual Fuzzy RGB Components

The algorithm computes the fuzzy weight for each individual fuzzy RGB component, based on their specific characteristics within the frame. Fuzzy logic principles are applied to assign appropriate weights [23] to these components.

$$F_R = \frac{[r - min(r)]}{[max(r) - min(r)]} \tag{1}$$

$$F_G = \frac{[g - min(g)]}{[max(g) - min(g)]} \tag{2}$$

$$F_B = \frac{[b - min(b)]}{[max(b) - min(b)]} \tag{3}$$

D. Step 4: Calculate Total Weight

1) Weight Aggregation

This step involves the aggregation of the individual fuzzy weights, resulting in the computation of the total weight of the fuzzy RGB frame. The total weight represents a consolidated measure of the frame's characteristics [23].

$$M_{F_C} = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{4}$$

E. Step 5: Calculate Individual Channel Weights

1) R, G, and B Components

The algorithm computes individual weights for the Red (R), Green (G), and Blue (B) components. These weights are calculated with consideration for the unique attributes and characteristics of each channel.

$$W_C = \frac{1}{N}\sum_{i=1}^{N} F_C \tag{5}$$

where W_c shows the weight of R, G and B channels.

F. Step 6: Create a Fuzzy Inference System (FIS)

1) Linguistic Variable Definitions

The algorithm defines the linguistic variables used within the Fuzzy Inference System (FIS). Key linguistic variables include $'Weight'$ (Low, Medium, High) and $'Iout'$ (Low, Medium, High).

2) Membership Functions

Fuzzy membership functions are rigorously defined for each linguistic variable, providing clear distinctions between various membership levels. For instance, $'Weight(W)'$ features membership functions such as $'Low'$ (a triangular function with parameters 0, 0.15, and 3), $'Medium'$ (parameters 0.25, 0.35, and 0.40), and $'High'$ (parameters 0.4, 0.7, and 1).

3) Rule Base

A comprehensive set of fuzzy rules is established to facilitate the mapping of input (Weight) to output (enhanced image) through the FIS. For example, the rule "If Weight is Low, then Iout is Dark" is a pivotal component of the rule base. Following rules are developed in the proposed approach:

r1="If Weight is Low then Iout is Dark";

r2="If Weight is Medium then Iout is Darker";

r3="If Weight is High then Iout is Bright";

G. Step 7: Combine the Three Channels

1) Color Frame Creation

The algorithm combines the enhanced R, G, and B components to create a comprehensive color frame. This integration ensures that the enhanced components are appropriately balanced, resulting in a visually coherent output.

H. Step 8: Create Video and Evaluate Performance

1) Video Compilation

A complete video is generated from the series of enhanced frames, presenting the viewer with a seamless and visually improved underwater video.

2) Performance Assessment

The algorithm rigorously evaluates the overall performance of the enhancement, considering factors such as image quality, clarity, and the extent to which visibility in underwater scenes is improved.

I. Step 9: Post-Processing

1) Additional Enhancement

If required, post-processing techniques are applied to further refine the enhanced video. These may include noise reduction, color correction, or other image enhancement procedures.

This algorithm represents a comprehensive and technically sound approach to enhancing underwater videos using Adaptive Fuzzy Weight Evaluation. It offers a systematic framework, wherein specific parameters, fuzzy membership functions, and rules can be fine-tuned to cater to the unique characteristics of underwater environments and achieve desired enhancement outcomes.

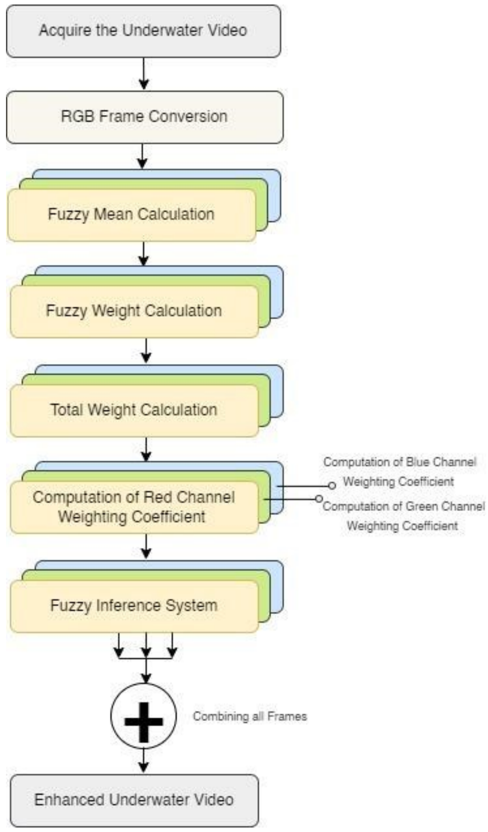

Fig. 1. Proposed algorithm

IV. RESULTS AND DISCUSSION

This section details experimental results and discussions obtained using Fish4Knowlege video database. Adaptive channel weights (R, G and B channels) are adaptively computed using a fuzzy inference system. The underwater sequence RGB components are not equally distorted and blurred with low contrast. So, the same amount of enhancement factor is not suitable for underwater scene improvement. Hence, this study presents an adaptive channel weight assignment strategy based on fuzzy logic.

The Fish4Knowledge dataset [22] is a valuable resource in the field of marine biology and computer vision. It comprises a diverse collection of underwater videos and images, primarily focused on fish species in various aquatic environments. This dataset serves as a crucial tool for researchers and scientists, enabling them to study marine life, behavior, and ecosystems. With its extensive and high-quality content, the Fish4Knowledge dataset contributes significantly to advancing our understanding of underwater biodiversity and environmental conservation efforts.

The dataset, which is of 200 TB size, consists of two subsets: a 10 minute video clip from all working cameras taken at 08:00 every day in the project and 690 video clips from the 9 cameras.

Fig. 2 depicts input and output membership functions employed for fuzzy conversion of input and output. The channel weight is modeled using three different membership functions: low, medium and high. In response the FIS generates output using: darker, dark and bright. Fig. 3 illustrates RGB histogram of input blurred low contrast frame. We can observe the red channel is centered whereas it is absent at low and higher pixel range. This is shown in Fig. 4. Fig. 4 shows the independent RGB component of the original underwater image.

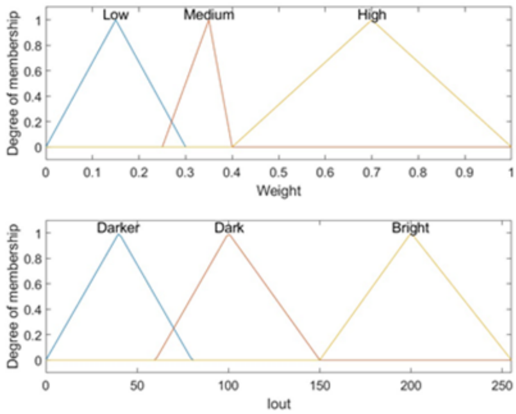

Fig. 2. Fuzzy membership function

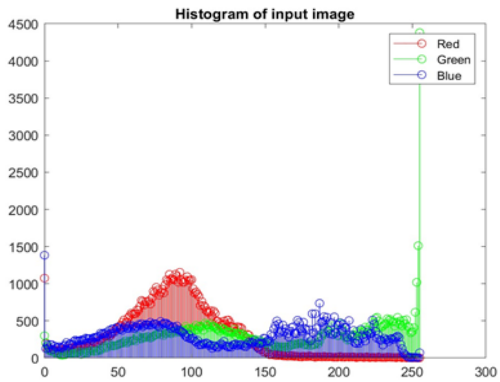

Fig. 3. Histogram of the input image

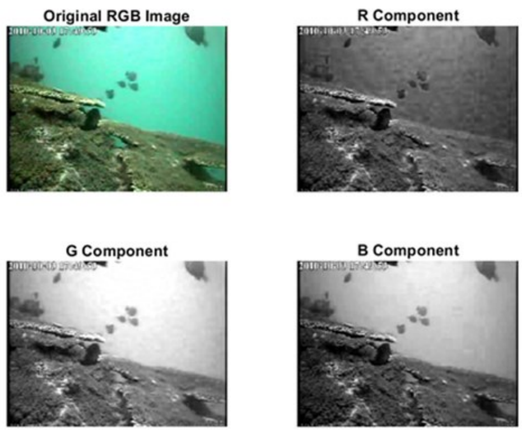

Fig. 4. Original image and RGB component

Fig. 5 illustrates enhanced underwater video frames using the proposed adaptive fuzzy contrast enhancement approach. As it is evident from the figure, the original red channel is improved significantly using the proposed technique. Furthermore, Fig. 6 shows RGB color histograms of enhanced frames. The improved histogram shows wider gray scale pixel distribution as compared to the original low contrast histogram.

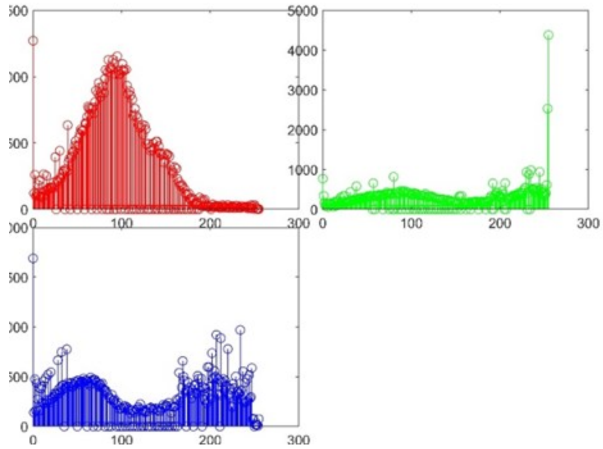

Fig. 5. Enhanced underwater video frame using adaptive fuzzy contrast enhancement

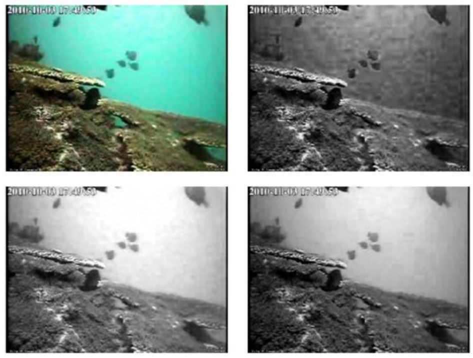

Fig. 6. Comparison of RGB color histograms: enhanced vs. original frame

Table I provides a comprehensive quantitative assessment of different frames using both the Balanced Contrast Enhancement Technique (BCET) and Adaptive Contrast Enhancement (ACE) methods, in comparison with the proposed method. This assessment encompasses a range of essential parameters, including Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Entropy, and Structural Similarity Index (SSIM). The table serves as a detailed analysis of these metrics to evaluate the effectiveness and performance of the proposed method when compared to the BCET and ACE methods across various frames.

TABLE I. QUANTITATIVE ASSESSMENT RESULTS USING THE PROPOSED ALGORITHMS WITH VIDEO FRAMES

	Method	RMSE	PSNR	Entropy	SSIM
Frame 1	BCET	31.80	18.02	7.82	0.531
	ACE	26.12	20.83	7.86	0.827
	Proposed	20.84	26.42	7.84	0.892
Frame 2	BCET	32.52	17.88	7.81	0.529
	ACE	24.36	20.39	7.85	0.792
	Proposed	18.43	25.89	7.84	0.872
Frame 3	BCET	32.72	17.83	7.76	0.516
	ACE	23.89	21.05	7.81	0.824
	Proposed	19.20	26.45	7.80	0.887
Frame 4	BCET	31.49	18.17	7.79	0.548
	ACE	24.10	20.19	7.82	0.814
	Proposed	18.98	25.49	7.83	0.891
Frame 5	BCET	31.93	18.05	7.82	0.539
	ACE	24.56	21.20	7.84	0.837
	Proposed	19.06	25.86	7.84	0.882

Table II presents the results of a thorough quantitative assessment conducted using the proposed algorithms on video frames. In this evaluation, various methodologies [23,24,25,26] have been considered to gauge their impact and efficacy on the given video frames. This table furnishes an intricate analysis of the performance of the proposed algorithms in contrast to these diverse methodologies, offering valuable insights into their effectiveness and relative performance.

TABLE II. QUANTITATIVE ASSESSMENT RESULTS USING THE PROPOSED ALGORITHMS WITH VIDEO FRAMES

Frame	RMSE	PSNR	Entropy	SSIM
Method [23]				
1	29.4738	18.7421	7.8668	0.7212
2	29.5236	18.7274	7.8666	0.7252
3	29.4875	18.738	7.8659	0.7296
4	29.3263	18.7857	7.8683	0.7228
5	29.8174	18.6414	7.8672	0.7274
Average	29.5257	18.7269	7.867	0.7252
Method [24]				
1	24.9768	20.1801	7.7961	0.8965
2	25.7789	19.9055	7.794	0.8933
3	26.1943	19.7667	7.7921	0.892
4	24.7826	20.2479	7.8008	0.8979
5	24.5602	20.3262	7.7982	0.8999
Average	25.2586	20.0853	7.7963	0.8959
Method [25]				
1	21.3807	21.5304	7.8756	0.9298
2	21.5529	21.4607	7.8753	0.9297
3	21.5212	21.4735	7.8749	0.9296
4	21.5733	21.4525	7.8771	0.929
5	21.6127	21.4366	7.8769	0.9297
Average	21.5282	21.4707	7.876	0.9295
Method [26]				
1	15.1476	24.5239	7.8677	0.9485
2	15.2147	24.4855	7.8679	0.9475
3	15.1603	24.5167	7.8673	0.9487
4	15.2416	24.4702	7.8692	0.9475
5	15.1958	24.4964	7.8684	0.9494
Average	15.192	24.4985	7.8681	0.9483
Proposed Method				
1	20.84	26.42	7.84	0.892
2	18.43	25.89	7.84	0.872
3	19.20	26.45	7.80	0.887
4	18.98	25.49	7.83	0.891
5	19.06	25.86	7.84	0.882
Average	19.302	26.002	7.83	0.8848

Underwater video enhancement has wide-ranging applications, benefiting marine biology by aiding species identification and ecological research, enabling efficient underwater inspection for structural issues, supporting search and rescue operations with improved visibility, contributing to environmental monitoring of coral reefs and pollution assessment, enhancing archaeological exploration by documenting submerged sites, providing captivating visuals for entertainment and education, aiding surveillance in border control and naval operations, and improving underwater photography with enhanced clarity and color accuracy. These advancements contribute to scientific research, environmental conservation, and various industries.

The proposed underwater scene enhancement approach can be further modified by employing additional contrast enhancement approaches. The fusion approach can be explored in future work to combine color corrected and contrast enhanced images.

V. CONCLUSION

This work presented a new and effective approach for improving degraded videos with poor contrast and non-uniform illumination, based on the adaptive fuzzy channel weight coefficient-based method. The central objective of our research was to tackle the inherent challenges associated with underwater imaging, including poor visibility, color distortion, and noise. We aimed to develop a method that could significantly improve the perceptual quality of underwater video content, making it suitable for various underwater exploration, research, and industrial applications. It was observed that the integration of fuzzy logic into our enhancement algorithm has allowed us to create a system that can adapt and adjust enhancement parameters intelligently. This adaptability is crucial for addressing the diverse and dynamic conditions encountered in underwater environments. By combining the fuzzy inference system with the adaptive fuzzy channel weight coefficient-based method, we have ensured that color channels are weighted optimally, thereby optimizing the enhancement process and delivering superior results. The performance evaluation of our fuzzy enhancement algorithm on the Fish4Knowledge database revealed promising outcomes. Through the use of well-established quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), Structural Similarity Index (SSIM), Underwater Image Color Correction Metric (UICM), and Underwater Image Sharpness Metric (UISM), we quantitatively demonstrated the effectiveness of our method.

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