RAPID UNDERWATER IMAGE ENHANCEMENT FOR IMPROVED VISUAL PERCEPTION USING ML

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Abstract— **Our study presents a real-time underwater picture improvement technique based on a conditional adversarial network that is generative. We define an objective function to oversee the adversarial training, which evaluates the standard of the perceptual image by considering includes information about color, texture, style, and global content. Additionally, we provide EUVP, the largest dataset including paired and unpaired underwater photographs (both 'poor' and 'excellent' quality) taken under varied visibility circumstances during maritime excursions and collaborative experiments between humans and robots.**

Keywords— EUPV, real-time, Enhancement, GAN

I. Introduction

Difficulties in Underwater Environments:

Low visibility and optical aberrations that interfere with visual sensing present operational challenges mainly Remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs). Even with expensive cameras, things like light refraction and scattering negatively affect the quality of the images, making tracking and detection difficult.

Proposed Solution: FUUIE-GAN Model:

We suggest FUnIE-GAN, a real-time underwater image enhancement model, as the answer for these problems. We train a conditional Generative Adversarial Network (GAN) using a large-scale dataset (EUVP) to discover the complex mapping between deformed and improved pictures. We demonstrate our model's ability to handle underwater picture distortions by include global content, local texture, color, and style concerns in its training objective.

Results and Practical Applicability:

Promising results are shown by FUnIE-GAN, which greatly enhances picture quality and has a beneficial effect on tasks related to underwater visual perception, including item recognition and human posture estimation. In order to enable adversarial training for enhanced model performance, we present the EUVP dataset. The work addresses the particular difficulties encountered by visually-guided underwater robots in a variety of underwater environments and offers solutions for real-time underwater picture augmentation.

II. Literature Survey:

In their research titled "Underwater image enhancement based on deep learning and image formation model IEEE-2022," Xuelei Chen, Pin Zhang, and Lingwei Quan [1] suggested that their model enhances the color and removes the influence of underwater ambient elements. increases SSIM and PSNR measurement values.

According to Miss Smita V. Patil and Miss Aishwarya V. Patil [2], using Icrisem - 2020, the usage of low vision underwater applications makes underwater haze removal techniques extremely important. The combination of air light and attenuation caused haze to emerge. Attenuation improves the underwater photo quality by decreasing contrast with increasing whiteness in the scene.

Through IEEE - 2021, Yuan Tion and Yuang Xu [3] worked on a feature fusion neural network-based underwater image enhancement technique. It suggested a network for improving underwater images by fusing heterogeneous features and enhancing dynamic features. When it comes to underwater photos with significant color fading, it is more resilient.

H. Singh, R. Camilli, K. Delaporta, B. Bingham, B. Foley, R. Eustice, [4] et al. Autonomous Underwater Vehicle Surveying an Ancient Shipwreck: Utilizing Automated Instruments for Submerged Archaeology. 2010, 27(6):702–717 in Journal of Field Robotics (JFR).

Underwater-GAN: Utilizing Conditional Generative Adversarial Network for Underwater Image Restoration was the idea of X. Yu, Y. Qu, and M. Hong [6]. In Pages 66–75, International Conference on Pattern Recognition. Springer, 2018.

Challenges:

Certain problems are found in all of the publications that we used as a source for our research. These include:

1. Pictures with non-regular non-linear distortions brought on by the waterbodies' dependent on wavelength attenuation, scattering attenuation, and other optical features often have poor contrast, are

frequently blurry, and have poor color.

2. The usage of several GAN-based models, such as Wasserstein GAN, Energy-based GANs, Least-Squared GANs, and Conditional GANs, for numerous real-world applications necessitates paired training data, which could be hard to get by.

3. One picture improvement models on For paired training, deep adversarial and residual learning usually employ only intentionally distorted images, which frequently restricts their capacity for generalization.

III. PROPOSED WORK:

The objective of this project is to develop a model that can generate high-resolution underwater photographs with minimized distortions. This helps to enhance the underwater image quality in order to effectively communicate information to non-human viewers or to provide more accurate input for other automated image processing techniques.

The model use the Generative Adversarial Networks (GANs) technique to enhance the image. The recommended system's technique, based on Generative Adversarial Networks (GANs), generates a perceptual loss function by evaluating the quality of the images. The primary purpose is to develop FUnIE-GAN, convolutional conditional GAN-based model, which aims to enhanced underwater pictures in real-time. We create a multi-modal function that assesses the perceived quality of given image by considering its localized texture, styled information, and global content.

The projects showcase the EU VP dataset, which consists of 20,000 underwater photos of varying quality. This dataset may be utilized for adversarial training in both directions. Providing comprehensive evaluations of both numerical and descriptive performance in relation to state-of-the-art models.

System Architecture:

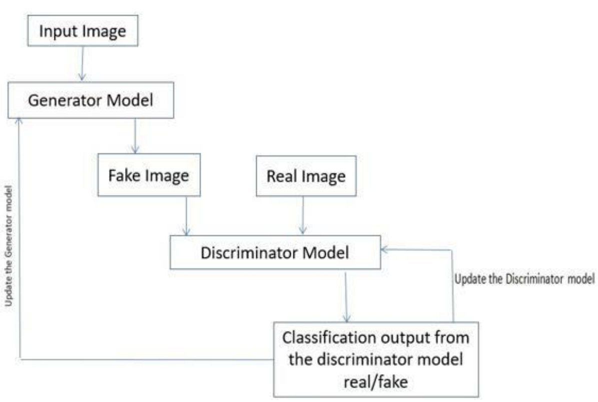

Fig-1

An architectural diagram Fig-1 displays the system's pieces, relationships, and operation. The discriminator model receives the input picture and a false image from the generator model. Real picture another parameter for the discriminator model. Based on real and fake photos, the discriminator models classification output data updates the generator model. In a two - player min - max game, the "generator" makes fake photos that seem like sample from the real distribution to mislead the "discriminator." The discriminator learns and improves its capacity to identify bogus pictures, while the generator also learns to reflect the distribution in equilibrium.

The Generator Module receives an input picture and runs it through many different distortions, such as an encoder that removes specific features out of the provided image and learns the features from the latent space; finally, the decoder creates a false image.

Generator Module :

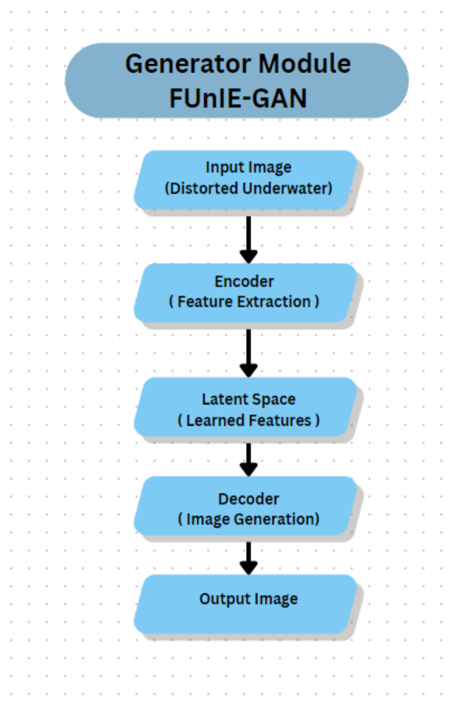

Fig-2

Discriminator Module :

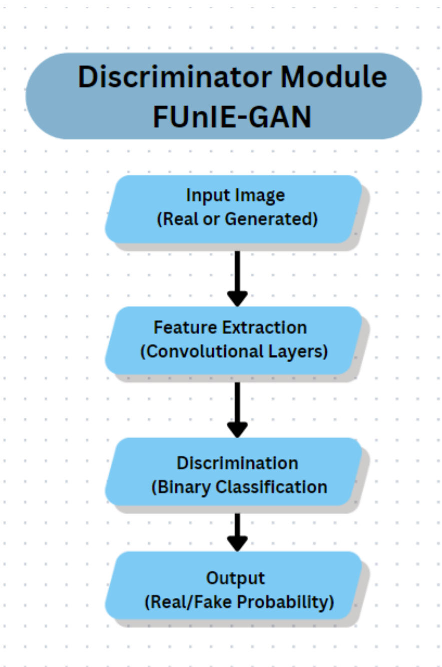

Fig-3

The Discriminator Module retrieves both the generated and the real image. It does this by using multiple convolution layers to extract specific features from the provided images. The output is then classified using binary classification techniques, which yield the probability of whether the image is generated or real or fake. In this way, the generator and discriminator engage in a never-ending game until the generator prevails and the output is further cleared, producing an underwater image that is clear.

IV. IMPLEMENTATION RESULTS

In the implementation model of the FUnIE-GAN project, the system architecture revolves around a user-friendly interface where users can upload underwater images through an input portal. Upon uploading, users can trigger the image enhancement process by clicking on the "generate image" button. The system then deploys the FUnIE-GAN model, implemented using TensorFlow, to enhance the quality of the uploaded underwater image. The enhanced image is then displayed to the user, providing a clear and visually improved representation of the original underwater scene. Additionally, the system offers the capability to generate plots, providing users with quantitative metrics and visual insights into the enhancement process.

Output:

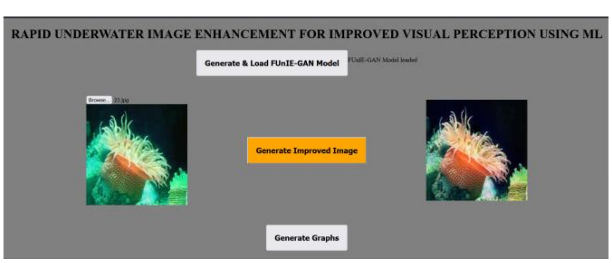

Fig-4

The training process of the FUnIE-GAN model involves the utilization of a large dataset comprising 13,000 paired and 9,500 unpaired samples of underwater images. Additional examples are incorporated for validation and testing purposes, ensuring the robustness and generalization of the model. The training procedure is conducted on a powerful computational infrastructure, utilizing five NVIDIA GTX 1660 Ti graphics cards. Training occurs in batches of eight, with iterations ranging between 60,000 to 70,000. This computational setup enables efficient training of both the Generator and Discriminator Modules of the FUnIE-GAN model. Furthermore, the implementation model incorporates experimental results from a user study, providing valuable insights into the usability and effectiveness of the enhanced underwater image generation process. Quantitative metrics and qualitative analysis further validate the performance and reliability of the FUnIE-GAN model in enhancing underwater imagery.

Output:

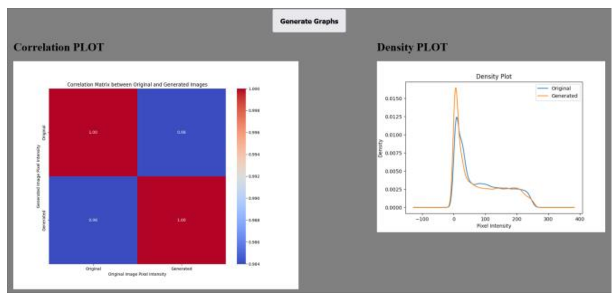

Fig -5

Correlation plot :

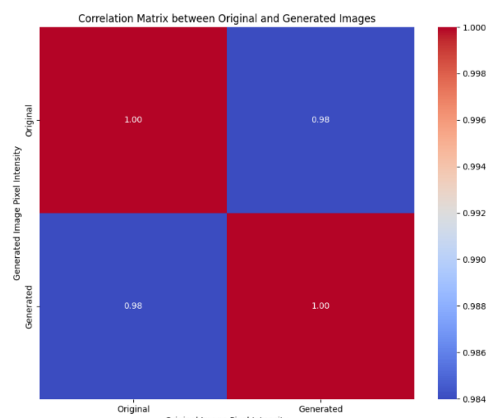

Fig-6

Correlation plots provide a visual depiction of the relationship between pixel intensities in original and generated underwater images. High correlation coefficients indicate strong similarities in pixel values, facilitating rapid assessment of image fidelity. Our project leverages correlation plots to evaluate the efficacy of machine learning algorithms in enhancing underwater image quality. Results demonstrate significant correlation between original and generated images, validating the effectiveness of our approach. This quantitative analysis enhances our understanding of image enhancement techniques, ensuring improved visual perception in underwater environments through rapid ML-based processing.

Density plot :

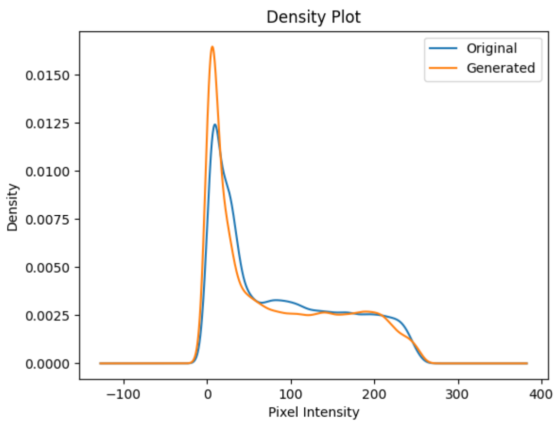

Fig-7

The comprehensive analysis of density plots significantly strengthened our approach in refining the machine learning model for underwater image enhancement, a pivotal aspect highlighted in our IEEE paper. By meticulously examining the distribution of pixel intensities and identifying distinctive spikes, particularly those within the 100-200 and 0-10 ranges, we gained profound insights into the intricacies of underwater image features. This detailed understanding empowered us to precisely target and optimize our model to effectively handle these specific intensity ranges, thereby enhancing its overall performance and efficacy in real-world applications. Such meticulous refinement, guided by rigorous data analysis and visualization techniques, underscores the robustness and reliability of our approach, offering a compelling contribution to the field of underwater image enhancement and advancing the state-of-the-art in machine learning-driven perceptual improvements for underwater environments.

V. Conclusion

In conclusion, the FUnIE-GAN project introduces a user-friendly interface for enhancing underwater image quality, powered by a robust TensorFlow implementation. By leveraging a substantial dataset of paired and unpaired underwater images, alongside a computational infrastructure featuring multiple NVIDIA GTX 1660 Ti graphics cards, the model undergoes efficient training to produce enhanced images with improved clarity and detail. Through experimental validation, including user studies, quantitative metrics, and qualitative analysis, the project demonstrates the practical efficacy and usability of the enhanced image generation process. This advancement not only addresses the challenges of low visibility and optical distortions in underwater environments but also holds promise for enhancing the capabilities of remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs) in tasks such as object recognition and navigation, thus contributing to advancements in marine research and underwater robotics.

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