INDIAN INSTITUTE OF TECHNOLOGY, GUWAHATI

INTERNSHIP REPORT

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Project Overview

During my internship at IITG, I had the privilege of working on a challenging project focused on enhancing underwater images. This report provides a detailed account of the project, its methodologies, and the outcomes achieved, with an emphasis on explaining key terms and concepts.

Understanding Underwater Image Enhancement:

Underwater Imagery

Underwater imagery refers to images or videos captured in aquatic environments, such as oceans, rivers, or lakes. These images often suffer from degradation due to various factors, including water turbidity, limited visibility, and color absorption. Enhancing the quality of underwater images is essential for applications like marine research, underwater archaeology, and industrial inspections.

Image Enhancement

Image enhancement is the process of improving the visual quality of an image to make it more suitable for human perception or machine analysis. Enhancements may involve adjusting image properties such as brightness, contrast, sharpness, and color balance.

Degradation Effects

In the context of underwater images, degradation effects are factors that degrade image quality. These effects can include:

- Illumination: Variations in lighting conditions underwater.
- Low Contrast: Reduced differentiation between objects and their background.
- Color Cast: Unwanted color shifts in images.
- Noisy: Presence of random, unwanted elements in the image.
- Blurred: Loss of image sharpness and details.
- Foggy: Simulation of foggy conditions underwater.
- Desaturated: Reduction in image color intensity.

FUnIE-GAN

FUnIE-GAN is an image enhancement model that employs Generative Adversarial Networks (GANs) to enhance the quality of underwater images. It stands out by integrating and fusing multiple GANs to improve image clarity, reduce noise, and enhance colors in underwater imagery.

Project Objectives:

The project's primary objectives were as follows:

1. Extract frames from underwater videos to create an initial dataset.

2. Simulate various underwater degradation effects on the extracted frames.

3. Evaluate the performance of the FUnIE-GAN model in enhancing underwater images.

4. Compare the results with two benchmark datasets, EUVP and UIEB.

Project Methodology:

1. Data Collection

The initial step involved the collection of underwater images by extracting frames from underwater videos available on the internet. These videos served as the source of the original images. The frames were extracted at a rate of 30 frames per second (fps), generating a substantial dataset of original images.

2. Simulating Underwater Conditions

To create the custom dataset of degraded images, a range of degradation effects was applied to the original images. These effects included:

- Illumination: Adjusting the illumination of images to mimic variations in underwater lighting.

- Low Contrast: Reducing image contrast to simulate the challenges of differentiating objects in low-visibility conditions.

- Color Cast: Introducing color casts to the images to represent color shifts underwater.

- Noisy: Adding random noise to the images to emulate the presence of particles in the water.

- Blurred: Applying Gaussian blur to the images to replicate the loss of sharpness and details.

- Foggy: Simulating foggy conditions by introducing haze and reducing image clarity.

- Desaturated: Reducing image color saturation to match the muted colors often observed underwater.

The degraded images were organized into subfolders under the 'Degraded' directory, each corresponding to a specific degradation effect.

3. Model Testing

For image enhancement and evaluation, a pre-trained image enhancement model called FUnIE-GAN was utilized. The model was loaded from a saved checkpoint, which included both the model architecture and weights. The model's primary objective was to enhance the quality of the degraded underwater images, effectively reducing the impact of degradation effects.

4. Evaluation and Comparison

The evaluation process involved assessing the quality of the enhanced images using two key metrics:

- Mean Squared Error (MSE): This metric provides a quantitative measure of the difference between the original and enhanced images. A lower MSE indicates a higher degree of similarity between the two.

- Peak Signal-to-Noise Ratio (PSNR): PSNR is a metric used to assess image quality in terms of noise and distortion. A higher PSNR value suggests better image quality and less distortion.

<u>Results and Findings</u>:

EUVP Dataset

- Number of Images Tested: 890
- MSE: 572.4187
- PSNR: 23.6083

UIEB Dataset

- Number of Images Tested: 890
- MSE: 812.5887
- PSNR: 21.3973

Degraded' Dataset

- Number of Images Tested: 890
- MSE: 262.7021
- PSNR: 26.1286

The results indicate that the custom 'Degraded' dataset, which simulates various underwater conditions, achieved the lowest MSE and the highest PSNR among the tested datasets. This suggests that the FUnIE-GAN model was more effective when applied to images with simulated underwater degradation effects. It was successful in mitigating the impact of these effects and enhancing image quality.

Conclusion and Insights:

The project provided valuable insights into underwater image enhancement and the effectiveness of the FUnIE-GAN model. Key takeaways include:

- Custom datasets that simulate underwater degradation effects can be invaluable for assessing image enhancement models, especially in underwater applications.

- FUnIE-GAN outperformed benchmark datasets (EUVP and UIEB) in terms of MSE and PSNR, indicating its effectiveness in enhancing underwater images.

Future Directions

The project opens up numerous opportunities for further research and development in the field of underwater image enhancement. Potential future directions include:

- Exploring additional degradation effects and their impact on image enhancement, allowing for a more comprehensive understanding of underwater conditions.

- Investigating the use of alternative image enhancement models and techniques, which could lead to improved results and broader applications.

- Real-world testing and deployment of image enhancement solutions for underwater applications, such as marine research, underwater robotics, and industrial inspections.

Acknowledgments

I would like to extend my heartfelt gratitude to the faculty and staff at IITG for their unwavering support and guidance throughout my internship. This project has not only enriched my knowledge of image processing and computer vision but also opened the door to exciting possibilities in the field of underwater image enhancement.

This internship has been a valuable learning experience, and I look forward to continued exploration and collaboration in this fascinating domain.

Please feel free to reach out if you have any further questions or require additional information.

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Project Link:

GitHub: https://github.com/dev-kabir/Underwater-Image-Enhancement.git

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