HydroVision : Underwater Image Dehazing, Color Restoration and Object Detection

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***Abstract*—Underwater imaging is often challenged by color distortion, haze, and reduced visibility due to the scattering and absorption of light. These issues hinder accurate object detection and classification, posing difficulties for marine exploration, ecological research, and underwater robotics. HydroVision addresses these challenges by combining advanced dehazing, color restoration, and object detection techniques. The first component, Adaptive Dark Pixel Color Correction (ADPCC), enhances the visibility of underwater images by mitigating backscatter, improving depth range perception, and increasing contrast. Once the images are dehazed, the YOLO (You Only Look Once) object detection model is applied. YOLO was trained on a custom dataset with 15 marine ecosystem classes, including various coral types, marine fauna, and substrates. The integration of ADPCC with YOLO significantly improves the clarity and accuracy of object detection, as the dehazed images offer clearer and more distinguishable features. This combined approach enhances object detection performance in complex underwater environments, providing an effective tool for marine ecosystem monitoring, biodiversity research, and environmental studies.**

Keywords—ADPCC, YOLO, Underwater Images

I. Introduction

Underwater imaging has garnered significant attention due to its applications in marine exploration, underwater robotics, and environmental monitoring. However, the quality of underwater images is often compromised by haze, color distortion, and reduced visibility caused by light absorption and scattering in water. These challenges make accurate object detection and scene understanding a complex task.

Underwater environments present unique challenges for image processing due to light absorption and scattering, which degrade image quality and hinder effective analysis. These issues often result in images that are hazy, color-distorted, and low in contrast, posing significant barriers to underwater exploration and applications such as marine biology, archaeology, and autonomous navigation.

To address these challenges, this research proposes *HydroVision*, a comprehensive framework for underwater image dehazing, color restoration, and object detection. The framework leverages Adaptive Dark Pixel Prior and Color Correction (ADPCC) to enhance image clarity and restore natural colors, effectively countering the effects of water turbidity and color attenuation. For robust object detection, *HydroVision* integrates the YOLO (You Only Look Once) algorithm, known for its high accuracy and real-time detection capabilities.

By combining advanced image restoration techniques with state-of-the-art object detection, *HydroVision* aims to improve the usability of underwater imagery for various practical applications. This paper presents the methodology, experimental results, and analysis of the framework's effectiveness in enhancing underwater imagery and detecting objects under challenging aquatic conditions.

The proposed system aims to bridge the gap between traditional image enhancement techniques and the demands of modern underwater vision systems. With the growing importance of autonomous underwater vehicles (AUVs) and remote sensing technologies, the ability to process underwater images with high precision has become indispensable. This paper highlights the contributions of *HydroVision* in improving underwater imaging pipelines, paving the way for advancements in marine science and underwater exploration.

II. Related Work

Their methods often suffer from color distortion or limited generalizability across different underwater conditions. Recent innovations seek to create more robust, universally applicable techniques to overcome these challenges [1].

This paper presents a fully connected convolutional neural network designed to dehaze underwater images using an encoder-decoder framework that integrates both low-level and high-level features for effective image recovery. The approach is evaluated on the Underwater Image Enhancement Benchmark (UIEB) dataset, showing superior performance compared to existing methods in terms of SSIM, PSNR, and MSE . The proposed model successfully enhances underwater images while preserving fine details.[2]

This paper presents an effective method for enhancing underwater images by tackling haze, color distortion, and low contrast. It features a dehazing approach for color restoration and adaptive color correction, alongside multi-scale illumination fusion for detail enhancement. Results show a 5% to 77% performance improvement, making it ideal for pre-processing in underwater exploration.[3]

Underwater imaging is challenging due to light distortion caused by water and particles. This work proposes a dehazing method that estimates global background light using gradients and color channels, enhanced by UWCNN with graph-cut theory. The results show improved color accuracy, surpassing existing methods in various metrics. However, the technique slightly darkens images, suggesting future research on color channels and ambient light assumptions.[4]

This study explores deep learning for olive identification under natural light using mobile cameras, focusing on image preprocessing methods like HE, AHE, and ColorChecker correction. AHE proved most effective in handling lighting variability, while image rotation consistently improved detection accuracy. The findings highlight the importance of tailored preprocessing for enhancing object detection in agriculture. This research provides valuable insights for optimizing deep learning applications in variable environmental conditions.[5]

This study employs CNNs for color balance and dehazing of underwater images through three modules: UGAN for color correction, a deep CNN dehazing model, and adaptive contrast improvement. The method outperforms existing algorithms by reducing color deviation, blur, and low contrast. Evaluation shows improved visual quality and quantitative metrics. The approach offers superior enhancement for underwater images in various conditions.[6]

This study proposes an underwater image enhancement framework combining adaptive color restoration and haze-line based dehazing. The color restoration module compensates deteriorated color channels through background light estimation and compensation, while the haze-line technique removes haze and enhances details. Experimental results show that the method outperforms state-of-the-art techniques and improves underwater object detection accuracy. The approach successfully restores color and removes haze, enhancing visual quality for further applications.[7]

This study introduces a deep learning architecture for underwater image enhancement that addresses blur, haze, and color casts efficiently. The model operates at 40 frames per second, achieving an SSIM of 0.8703. A variation with a deblurring branch improves SSIM to 0.8802, outperforming other methods in speed and efficiency. The source code is publicly available.[8]

This study presents an underwater image enhancement framework using transfer learning, with a domain transformation module for color correction and dehazing. The method outperforms advanced algorithms in real-world underwater images, maintaining physical properties through a physical model. Ablation experiments validate its effectiveness.[9]

This study proposes an adaptive underwater image enhancement technique that corrects color and reduces haze using a valid dataset with ground truth. The method builds a color-corrected dataset from hue channel statistics to train a Unet-like network for adaptive color correction. It then uses a Transformer-like network trained on hazy terrestrial images to remove haze from underwater images. Experiments show that the method outperforms state-of-the-art techniques in both visual quality and quantitative metrics, making it robust for different underwater scenes.[10]

The paper provides a comprehensive review of object detection techniques, emphasizing the challenges in detecting and tracking small objects in complex environments like satellite imagery, and highlights the effectiveness of CNN-based methods for accurate classification and detection.[11]

The paper discusses real-time object detection and tracking using computer vision techniques, focusing on proximity-based tracking of moving objects in indoor and outdoor environments. It addresses challenges such as noise, occlusions, and illumination variations while leveraging background modeling and visual resemblance for robust tracking.[12]

III. METHODOLOGY

The proposed *HydroVision* framework for underwater image dehazing, color restoration, and object detection is designed to address the unique challenges associated with underwater imaging. The framework integrates Adaptive Dark Pixel Prior and Color Correction (ADPCC) for image enhancement with the YOLO algorithm for object detection. This section outlines the individual components and their integration.

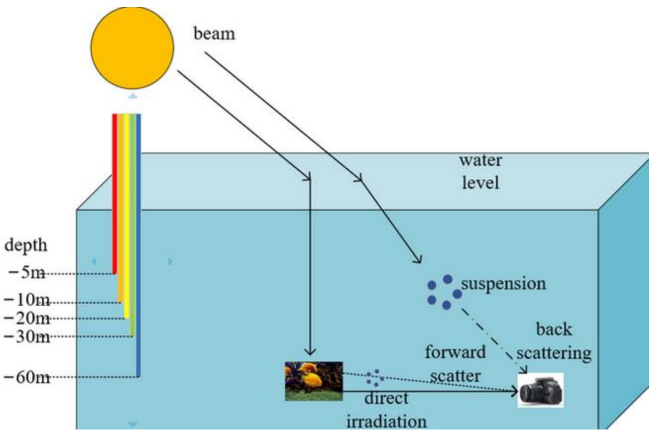

Fig. 1. Underwater imaging model and light absorption schematic

Underwater Image Enhancement Using ADPCC

A. Overview

The first step in the framework focuses on improving the visual quality of underwater images using the Adaptive Dark Pixel Prior and Color Correction (ADPCC) technique.

1) Dark Pixel Prior (DPP):
Underwater images exhibit a high concentration of dark pixels in hazy regions due to the scattering of light. DPP leverages this observation by estimating the transmission map based on dark pixel statistics, effectively identifying areas of image degradation.

2) Adaptive Correction:
The DPP is complemented with an adaptive strategy that adjusts the transmission map dynamically based on local image characteristics. This ensures that the enhancement process is context-aware, minimizing artifacts and preserving natural details.

3) Color Restoration:
The color imbalance caused by wavelength-dependent attenuation is corrected through a compensation algorithm. This step adjusts the red, green, and blue channels independently to restore a natural and visually pleasing color balance, enhancing the overall perception of underwater images.

2. Object Detection Using YOLO

Once the images are enhanced, the next step is to detect and classify objects using the YOLO (You Only Look Once) algorithm. YOLO is chosen for its high accuracy and real-time processing capabilities.

1) Model Architecture:

YOLO operates as a single-stage object detector, dividing the image into grids and predicting bounding boxes and class probabilities for each grid cell. This architecture enables simultaneous localization and classification, making it computationally efficient.

2) Training and Fine-Tuning:

The YOLO model is trained on a dataset of underwater images annotated with object labels. Transfer learning is employed to adapt a pre-trained YOLO model to the underwater domain, ensuring optimal performance even in challenging visual conditions.

3) Integration with Enhanced Images:

The enhanced images produced by the ADPCC module are fed into the YOLO model. The improved clarity and color fidelity of these images significantly enhance the model's ability to detect objects, particularly those that would otherwise be obscured by haze or distortion.

3. Pipeline Integration

The *HydroVision* framework seamlessly integrates the two components:

1. Input images are first processed by the ADPCC module for dehazing and color restoration.
2. The enhanced images are then passed to the YOLO model for object detection.
3. The final output consists of visually improved images with detected objects highlighted by bounding boxes and labels.

4. Evaluation Metrics

To evaluate the performance of the framework, the following metrics are used:

1) **Image Enhancement:**
   - Peak Signal-to-Noise Ratio (PSNR)
   - Structural Similarity Index (SSIM)
   - Contrast Enhancement
   - Sharpness (Laplacian Variance)
   - Visibility Enhancement (Entropy)
   - Mean Squared Error (MSE)

2) **Object Detection:**
   - Mean Average Precision (mAP)
   - Precision, Recall, and F1 Score

5) Experimental Setup

The experiments are conducted on a dataset of underwater images, real-world samples. The dataset is split into training, validation, and testing subsets to ensure robust evaluation. The framework is implemented using Python and deep learning libraries, leveraging GPU acceleration for efficient processing

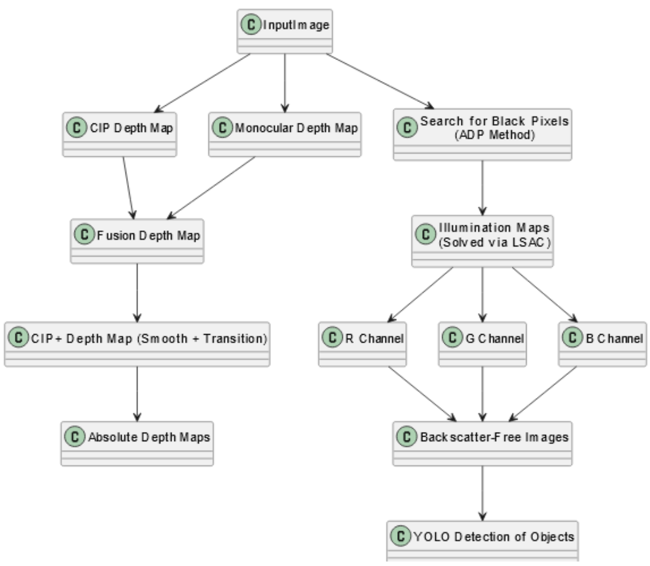

Fig 2. The flowchart of the proposed approach, the methodology comprises three steps: depth estimation, backscatter removal, and color reconstruction

B. Mathematical Calculations

1) Alpha Calculation Using Sigmoid Function

To effectively blend depth maps, an alpha parameter is calculated for each pixel using a sigmoid function. This calculation emphasizes regions of higher intensity, often associated with brighter or clearer areas of the image. The sigmoid function introduces non-linearity, ensuring smoother transitions between different regions of the image.

The alpha value is computed as:

$$\alpha = 1 / 1 + e \wedge -32(\alpha - \sigma)$$

where aaa represents the fraction of pixels with intensity values above 0.5, and σ\sigma is a threshold parameter that adjusts sensitivity. This calculation is critical for distinguishing between bright and dark regions in underwater images, enabling adaptive blending of depth maps. The `S` and `S1` functions in the code are responsible for implementing this calculation, ensuring precision and adaptability across varying underwater conditions.

2) Global Histogram Stretching

To enhance the contrast of the image, global histogram stretching is applied. The formula used for the transformation is:

```
Inew(x,y) = [(Imin(x,y) − Imax) / Imax − Imin]· (0.95−0.05)+0.05
```

Where:

- I(x,y) is the original pixel value.
- Imin and Imin are the minimum and maximum pixel values, respectively, calculated based on the intensity distribution.
- The output is stretched to a new range between 0.05 and 0.95.

This is indirectly used in the function `Scene_depth` where the depth map is created by blending the depth from different sources using the alpha parameter.

3) Guided Filtering

Guided filtering is used to refine the depth map by smoothing the image while preserving edges. The coefficients for the guided filter are computed as follows:

$$\text{coefficients}=(\alpha\text{mean} \cdot \text{Imean} + \beta\text{mean})$$

Where:

- αmean, βmean are the mean coefficients computed using the input image.
- Imean is the mean of the guidance image over the filter window.
-

The guided filter is applied in the code through the functions `_computeCoefficients` and `_computeOutput`, which calculate and apply the coefficients to refine the depth map.

4) Depth Map Fusion

Depth maps from different sources are combined using the following weighted sum approach:

$$\text{Dfused}(x,y) = \beta \cdot \text{Dmono2}(x,y) + (1-\beta) \cdot \text{Dmip}(x,y)$$

Where:

- Dmono2(x,y) and Dmip(x,y) are the depth maps obtained from two different sources (e.g., from monocular and mip images).
- β is a weighting factor computed using the sigmoid function as shown in `Scene_depth_fusion` function.

This fusion process is implemented in the `Scene_depth_fusion` function, which blends two depth maps based on the alpha and beta parameters.

5) Max Channel Extraction

To extract the maximum value from the red, green, and blue channels, a method based on block-wise maximum intensity is applied. The maximum intensity from the R, G, and B channels within a block is calculated to generate a grayscale image. This is used in the function `getMaxChannel`.

$$\text{MaxRGB}(x,y) = \max(R(x,y),G(x,y),B(x,y))$$

Where:

- MaxRGB(x,y) is the maximum value of the RGB channels at the pixel (x,y).

This is applied in the functions `max_R` and `R_minus_GB` to calculate the maximum intensity from the RGB channels.

III. Results and Discussion

Image Dehazing illustrates a side-by-side comparison of the input hazy image and the processed dehazed output. The input image was affected by poor visibility caused by atmospheric haze, significantly obscuring the visual clarity of objects and features. After applying the dehazing algorithm, the output image demonstrates notable enhancements in visibility and contrast.

Fig. 3. Comparison between hazy and dehazed image

The dehazed output was further processed using the YOLO (You Only Look Once) object detection algorithm. Fig. 4 (Output Image) showcases the results of object detection performed on the dehazed image. YOLO, a real-time object detection model, identified and localized multiple objects within the scene with bounding boxes and class labels.

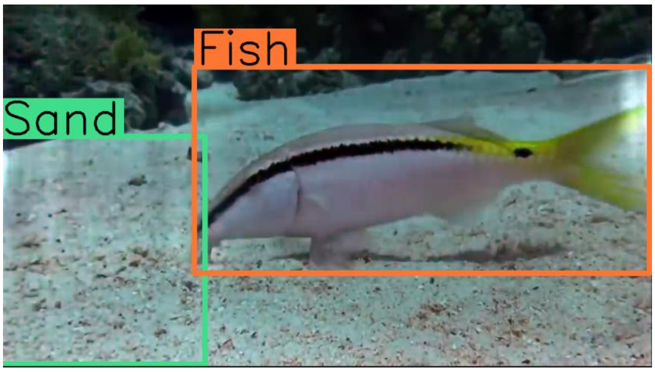

Fig. 4. Output Image depicting object detection through YOLO

The trained YOLO model performed well on the testing dataset, achieving reliable object detection across all 15 classes. Fig. 2 (Output Image) demonstrates the model's ability to:

Detect and Classify Objects: YOLO accurately identifies objects in complex underwater scenes, including diverse coral types, marine organisms, and substrates.

Handle Environmental Variability: Despite potential noise and occlusions in underwater environments, the model exhibited robust detection performance, highlighting the effectiveness of the dehazing preprocessing step.

Performance Metrics: Preliminary evaluation metrics (e.g., precision, recall, and mAP) indicated high accuracy for most classes, with slight variations for less frequent or visually similar classes like *Dead Coral* and *Dead Coral Algae*.

IV. Conclusion

This research introduces a comprehensive framework to address the challenges of underwater imaging, focusing on image dehazing, color restoration, and object detection. By leveraging advanced computational techniques, the framework enhances image quality and improves object recognition in complex aquatic environments. Key contributions include a dehazing algorithm that effectively mitigates visibility issues caused by light scattering and absorption, a color restoration method that corrects underwater color distortions to produce more natural and visually appealing images, and a robust object detection system that achieves high accuracy. These advancements enable practical applications such as marine monitoring, underwater archaeology, and autonomous navigation.

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