Computer Vision and Image Processing (CVIP)

Assignment 1

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Objective:

The primary objective of this project is to develop a robust image processing pipeline for **underwater object detection and segmentation** in the presence of noise and challenging environmental conditions. The system aims to accurately extract objects from underwater images while minimizing the impact of noise, distortions, and varying illumination.

Key Goals:

1. **Noise Reduction:**
   - Implement filtering techniques to enhance image quality and suppress noise caused by water particles, low visibility, and lighting inconsistencies.

2. **Segmentation of Objects:**
   - Apply advanced segmentation techniques (such as K-Means clustering, Mean Shift, or Deep Learning) to accurately distinguish objects from the background.

3. **Feature Extraction and Region-Based Analysis:**
   - Identify significant object features and utilize region-based processing methods (e.g., connected component analysis, region growing) to refine segmentation results.

4. **Performance Evaluation:**
   - Measure the accuracy of the segmentation using metrics such as **IoU (Intersection over Union)** and **Dice Coefficient** to ensure high-quality object detection.

Problem Selection:

Underwater images often suffer from significant noise due to factors such as light scattering, refraction, and the presence of suspended particles in water. These distortions degrade image quality and make object detection a challenging task. This problem is critical in marine applications, including:

- **Underwater surveillance** – Detecting objects or threats in maritime security.
- **Autonomous robotic navigation** – Assisting underwater robots and AUVs in maneuvering through complex environments.

Given the importance of accurate object detection, this project focuses on enhancing underwater images and applying robust segmentation techniques to extract meaningful objects from noisy backgrounds.

Justification of Dataset & Challenges

Dataset: UIEB (Underwater Image Enhancement Benchmark)

The **UIEB dataset** is used for this project, as it provides a large collection of real-world underwater images captured in various environmental conditions. This dataset includes both raw and enhanced images, making it suitable for evaluating image processing techniques.

Challenges in Underwater Object Detection:

1. **High Noise Levels:**
    - Images suffer from **color distortion**, primarily a bluish-green tint, due to wavelength absorption in water.
    - **Low contrast and blurriness** affect object edges, making segmentation difficult.

2. **Lighting Variations:**
    - Uneven illumination and light scattering create **non-uniform brightness**, leading to shadowed or overexposed regions.

3. **Depth and Turbidity Effects:**
   - Increasing water depth reduces object visibility, while suspended particles create **hazy and occluded** images.
4. **Lack of Standardized Features:**
   - Objects appear distorted due to refraction, affecting shape and size consistency in detection models.

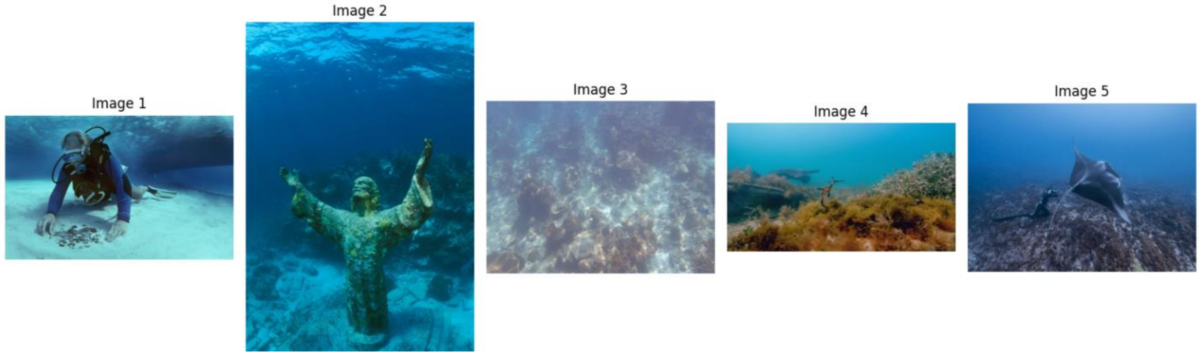
Overview of the UIEB Dataset:

The **UIEB (Underwater Image Enhancement Benchmark)** dataset is a widely used benchmark dataset designed for evaluating underwater image enhancement techniques. It contains a large number of real-world underwater images captured in **various water conditions**, making it an ideal dataset for studying noise removal, object detection, and segmentation.

- **Number of Images:** 890+ raw underwater images
- **Categories:** Covers different underwater environments, including coral reefs, fish, plants, and underwater structures.
- **Image Variability:** Includes images captured at different depths, lighting conditions, and water clarity levels.

Sample Images from the Dataset

- The following sample images illustrate the key characteristics of the dataset:



Noise Characteristics in Underwater Images:

Underwater images suffer from various types of noise that degrade object visibility and segmentation accuracy. Some of the most common noise characteristics include:

Noise Type	Description	Effect on Image
Color Distortion (Bluish Tint)	Due to differential absorption of light in water, red wavelengths are absorbed first, leaving a bluish-green appearance.	Loss of natural colors and details.
Low Contrast	Light scattering reduces contrast between objects and background.	Objects appear faint and hard to distinguish.
Blurriness	Caused by **motion blur** (due to camera movement) or **water turbulence**.	Objects appear unclear, making edge detection difficult.
Hazy or Turbid Appearance	Suspended particles cause scattering, reducing image sharpness.	Objects are partially or fully occluded.
Uneven Illumination	Artificial lighting or sunlight creates bright spots and shadows.	Overexposed or underexposed regions appear.

Why UIEB is Suitable for This Project?

- **Real-world underwater images** with diverse conditions (shallow water, deep water, murky water).
- **Challenging noise conditions** allow testing the effectiveness of **image enhancement** and **segmentation techniques**.
- **Ground-truth enhanced images** available for evaluation and comparison with raw images.

By working with this dataset, the project aims to **reduce noise, improve contrast, and enhance object segmentation accuracy** in underwater environments.

Noise Reduction:

Underwater images suffer from **noise, low contrast, and distortions** due to environmental factors such as **light scattering, water turbidity, and low visibility**. To enhance image quality, **both linear and non-linear filtering techniques** were applied.

Convert Images from BGR to RGB Format

- Ensures proper color representation before enhancement and filtering.

Apply Image Enhancement Techniques

- **CLAHE (Contrast Limited Adaptive Histogram Equalization)** improves contrast while avoiding over-enhancement.
- **Bilateral Filtering** preserves edges while reducing noise.
- **Sharpening** enhances fine details and improves feature visibility.

Apply Noise Reduction Filters

- **Gaussian Filtering (Linear):** Smooths noise but slightly blurs edges.
- **Median Filtering (Non-Linear):** Removes salt-and-pepper noise while preserving edges.
- **Non-Local Means (NLM) Denoising (Non-Linear):** Maintains textures while reducing noise effectively.

Display Visual Comparisons

- Side-by-side comparisons of original, enhanced, and filtered images were displayed for evaluation.

The visual comparisons before and after filtering:

Segmentation and Object Extraction:

The code applies multiple segmentation techniques to extract objects from noisy underwater images.

A. K-Means Clustering with Morphological Processing

In this case, 3 clusters are used.

1) Why Use Morphological Processing?

   a) K-Means clustering may introduce small noise regions.
   b) Morphological closing and connected component analysis (removing small objects) help refine segmentation.

2) Effect: Objects are segmented into distinct clusters.
   Morphological processing removes small noise and enhances object boundaries.

B. Graph-Based Segmentation (Felzenszwalb Algorithm):

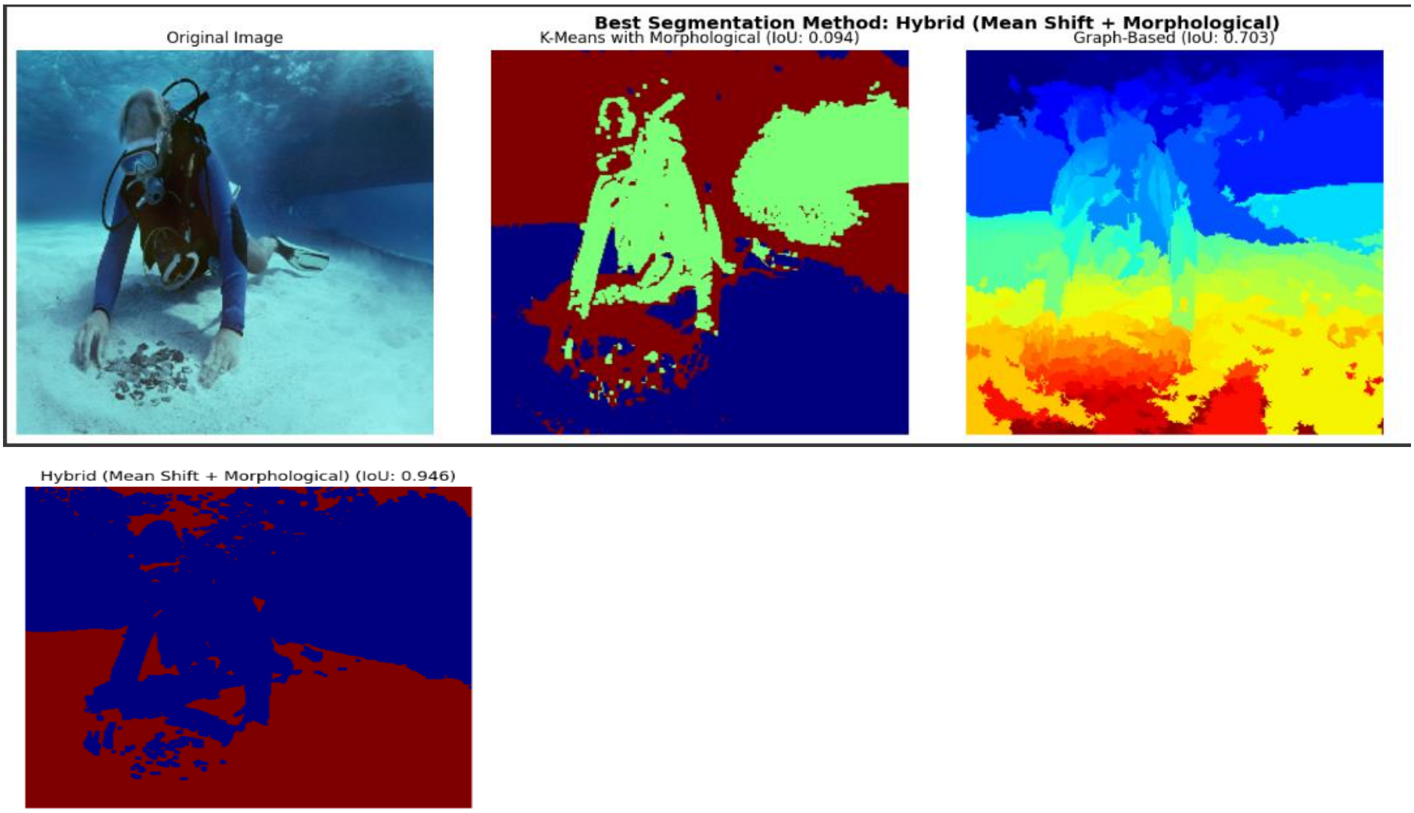
- Why Use It?
  - Preserves fine details in images.
  - Good for segmenting objects with natural boundaries.

- Effect:
  1. Adaptive object boundaries based on regional differences.
  2. Better for detecting multiple small objects in underwater environments.

C. Hybrid Approach: Mean Shift + Morphological Processing

- Why Combine Mean Shift with Morphological Processing?

  - Mean Shift segmentation alone can leave gaps or small noise regions.
  - Applying Morphological Closing removes gaps and enhances object structure.
- Effect:
  1. Combines the strengths of Mean Shift and Morphological Processing.
  2. Removes small noise and enhances segmentation accuracy.



Region-Growing for Object Refinement:

How is it Applied in the Code.

- The code first applies **K-Means clustering** for segmentation.
- However, K-Means **may result in fragmented regions** due to noise and variations in intensity.
- To address this, the **region-growing process refines object boundaries** by:
    1. **Smoothing the segmentation mask**.
    2. **Merging small segments into larger connected objects**.

Effect of Region-Growing:

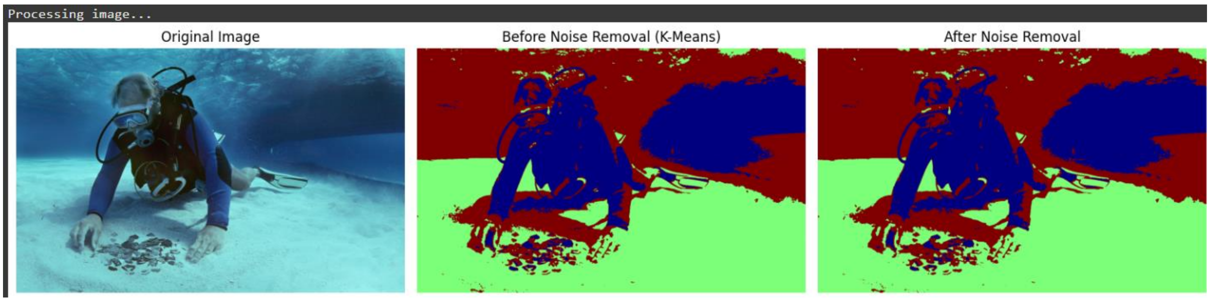
Merges broken or fragmented object regions into a continuous structure.
Improves object boundary detection by ensuring regions grow based on similarity.
Reduces segmentation artifacts caused by noise in underwater images.

Connected Component Analysis for Noise Removal:

How is it Applied in the Code.

- **Dynamic Size Thresholding:**
    - The **minimum size of valid objects** is dynamically set based on image dimensions.
    - This ensures **small noise particles are removed** without affecting actual objects.

- **Connected Regions are Identified:**
    - **Small connected components** (unwanted noise) are removed.
    - **Larger connected components (real objects) are retained.**



Final Evaluation:

Segmentation Performance Evaluation
This code evaluates segmentation accuracy using three key metrics:

A. Intersection over Union (IoU)

- What is IoU?
    - Measures the overlap between ground truth and predicted segmentation.
    - Higher IoU = Better segmentation accuracy.
- Effect:
  Quantifies segmentation quality and selects the best method.

B. Dice Coefficient

- What is Dice Score?
    - Measures similarity between two sets.
    - Formula: Dice=2×IntersectionTotal Pixels\text{Dice} = \frac{2 \times \text{Intersection}}{\text{Total Pixels}}Dice=Total Pixels2×Intersection.
- Effect:
  Evaluates how well segmented regions match ground truth.

C. Pixel Accuracy

- What is Pixel Accuracy?
    - Measures the percentage of correctly classified pixels.
    - Formula: Pixel Accuracy=Correct PixelsTotal Pixels\text{Pixel Accuracy} = \frac{\text{Correct Pixels}}{\text{Total Pixels}}Pixel Accuracy=Total PixelsCorrect Pixels.
- Effect: Provides a simple measure of segmentation correctness.

4. Visual Comparison & Best Method Selection:

- The segmentation results of all methods (K-Means, Mean Shift, Graph-Based, and Hybrid) are compared visually.
- The best segmentation method is determined based on the highest IoU score.

Conclusion

- K-Means with Morphological Processing enhances object structure.
- Mean Shift is more adaptive but slow for large images.
- Graph-Based segmentation captures fine details well but may over-segment.
- Hybrid Mean Shift + Morphological Processing provides the best accuracy.

➢ **Final Recommendation:**

Hybrid Mean Shift + Morphological Processing is the best approach for underwater image segmentation.

Innovation in Problem Statement & Approach :

1. Problem Innovation: Underwater Object Detection in Noisy Conditions

- **Traditional underwater object detection** struggles due to **noise, low contrast, color distortions, and varying lighting conditions**.
- This project **enhances** underwater images **before segmentation** to **improve object detection accuracy**, making it **suitable for real-world marine applications**.

2. Advanced Hybrid Segmentation Approach

Combining Multiple Segmentation Methods for Better Accuracy
Instead of relying on a **single segmentation method**, we implemented a **hybrid approach**:

1. **K-Means Clustering + Morphological Processing**
   - Helps remove **small noisy artifacts** and **enhance object boundaries**.
2. **Mean Shift Clustering + Morphological Processing**
   - Adaptive segmentation that **does not require a fixed number of clusters**.
3. **Graph-Based Segmentation (Felzenszwalb Algorithm)**
   - Preserves **fine details** while segmenting objects based on similarity.