UNDERWATER FUSION NET (UWFNET): A FUSION-BASED METHOD FOR UNDERWATER IMAGE ENHANCEMENT

UNDER DR. GEETHA S

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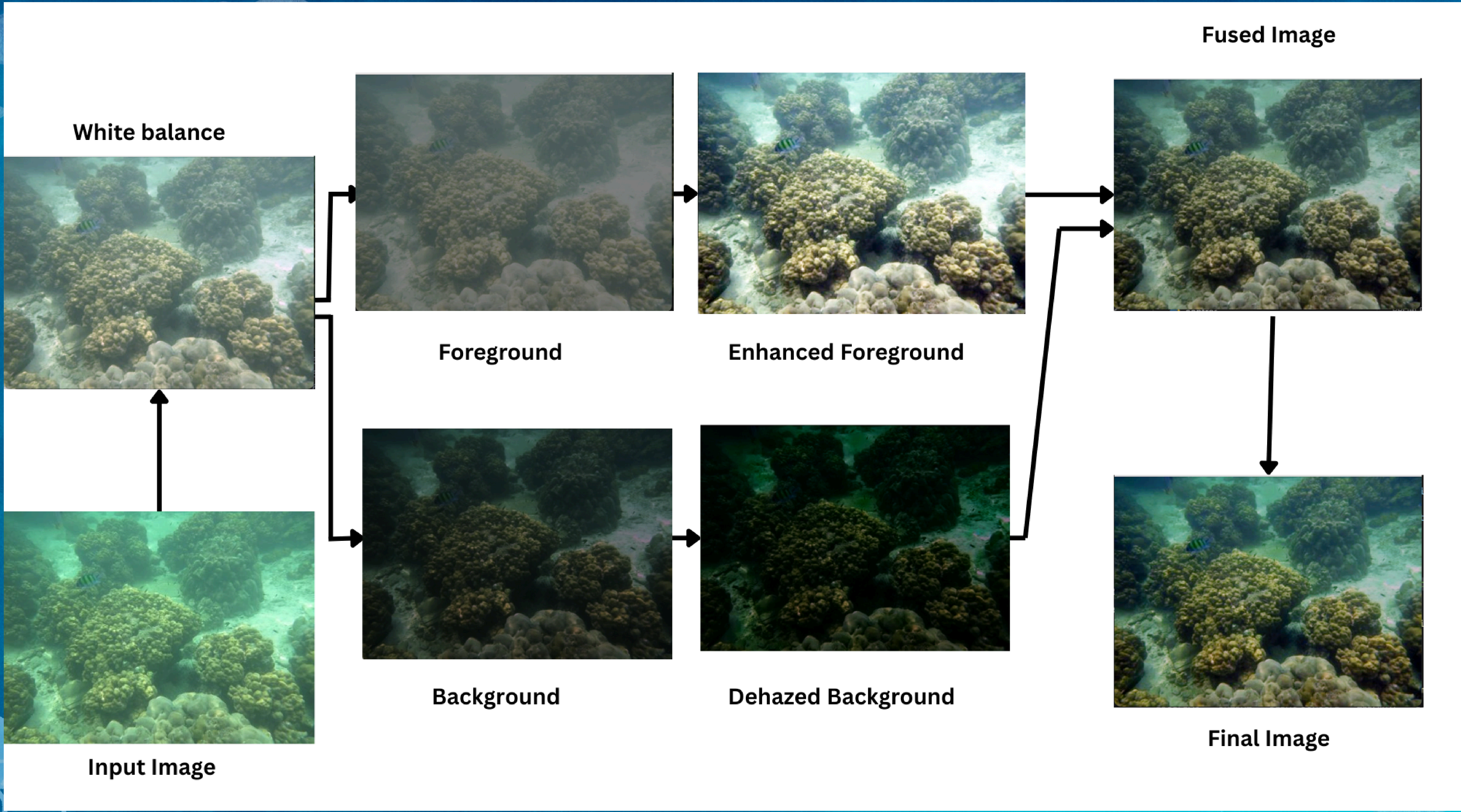
CONTENT

WHY DO UNDERWATER PICTURES LOOK BAD?

Let's take a look at some underwater pictures—selfies, marine life, and scenic rocks. But wait, why do they all look blurry and green?
It's not because of bad photography—there's a scientific reason!
Water is much denser than air, meaning that when light travels through it, it encounters more particles that scatter or absorb the light. This leads to:

✅ Scattering → Reduces contrast and makes images hazy.
✅ Absorption → Removes colors, especially red, making images appear blue or green.
No matter how advanced your camera is, these environmental factors will always degrade underwater images. So, how can we fix this? That's where Underwater Image Enhancement comes in!

METHODOLOGY



SOLUTION

We propose a novel modular pipeline, Under Water FusionNet (UWFNet), for underwater image enhancement.

Our method sequentially applies White Balancing, Image Decomposition, Contrast Enhancement, Dehazing, Image Fusion, and Color Refinement to produce high-quality, visually enhanced underwater images.

Each stage addresses a specific underwater degradation factor, resulting in a comprehensive and effective enhancement framework.

STEP 1: WHITE BALANCING

- Converts the image from BGR to LAB color space.
- Computes average chrominance components (a, b).
- Adjusts each pixel's a and b based on how far the average deviates from the neutral gray (128).
- Converts the corrected LAB image back to BGR.

Let:

a(x,y),b(x,y): chrominance channels (from LAB space)
L(x,y): lightness channel
a',b': mean of a and b over the entire image
Then, the adjusted chroma channels are:

$$a'(x,y) = a(x,y) - (\bar{a} - 128) \cdot \left(\frac{L(x,y)}{255}\right) \cdot 1.1$$

$$b'(x,y) = b(x,y) - (\bar{b} - 128) \cdot \left(\frac{L(x,y)}{255}\right) \cdot 1.1$$

This step reduces dominant blue or green tints in underwater images, bringing colors closer to natural tones.

STEP 2: IMAGE DECOMPOSITION FOR CONTRAST ENHANCEMENT & DEHAZING

Why Decomposition?

- Underwater images mix foreground and background elements, making enhancement challenging.
- Separating them helps apply different enhancement techniques effectively.

Decomposition: Color-corrected image split into foreground (IF) & background (IB) using a critical value k.

  - ○ Foreground Image: $I\_F = (1-k) * I\_cc(x, y)$
  - ○ Background Image: $I\_B = k * I\_cc(x, y)$ (where k = image separation factor)

Enhancement Steps

- Foreground: Contrast enhanced using percentile maximum-based method.
- Background: Dehazed using multilayer transmission map estimation.

Outcome

- Improved visibility & contrast in the foreground.
- Dehazed, clearer background for enhanced image quality.

◆ Key Benefit: Effective separation improves visual clarity in images.

STEP 3: CONTRAST ENHANCEMENT (FOREGROUND PROCESSING)

Why Contrast Enhancement?
Foreground elements appear dull due to underwater light scattering.
Enhancing contrast improves object visibility.

Proposed Enhancement Method

Percentile Maximum-Based Contrast Enhancement

- Identifies brightest and darkest pixels and adjusts pixel intensity distribution.

Step 1: Define Thresholds

- Low pixels raised to first threshold (improves shadows).
- High pixels reduced to second threshold (prevents overexposure).

Step 2: Pixel Adjustment Formula

- $V1 = (1 - y) \times A[x] + j \times A[x + 1]$
- $V2 = (1 - y) \times A[x] + y \times A[x + 1]$

Benefits

- Preserves image details while enhancing contrast.
- Maintains realistic textures without over-sharpening.

STEP 4: DEHAZING USING MULTILAYER TRANSMISSION MAP

Why is Dehazing Needed?

- Water scatters light, causing haze and reducing visibility.
- Traditional dehazing fails to handle varying depths accurately.

Proposed Dehazing Process

- Step 1: Compute Transmission Map
  - Estimates atmospheric light based on scene depth.
- Step 2: Apply Guided Filtering
  - Filters depth variations to remove artifacts.
- Mathematical Representation
  - $J(x) = (I_B(x) - A(1 - t(x))) / t(x)$ (where A = atmospheric light, t = transmission map)

Benefits

- Removes haze while retaining natural colors.
- Works at various water depths for better clarity.

STEP 5: ENTROPY BASED IMAGE FUSION

Why is Entropy-based Fusion Needed?

- Different images may contain varying levels of information (entropy).
- Traditional fusion methods may not effectively emphasize regions with higher information content.

Proposed Entropy-based Fusion Process

- Step 1: Compute Entropy of Images
- Measures the amount of information (uncertainty) in each image using a histogram-based approach.
- Step 2: Compute Weighted Fusion
- Combine the images by weighting them based on their entropy values, giving more importance to regions with higher information.

Mathematical Representation

$$fused\_image=(e1 \cdot image1+e2 \cdot image2)/(e1+e2)$$

Where e1 and e2 are the entropy values of image1 and image2

Benefits

- Emphasizes regions with high information and detail.
- Simple and efficient for enhancing textures and preserving image details.

DATASET DESCRIPTION

Here's your revised paragraph with the three benchmark datasets (UCCS, UIQS, UIEB) and their respective details:
In this work, we utilize three benchmark datasets—UCCS, UIQS, and UIEB—to evaluate the performance of our underwater image enhancement pipeline. The UCCS dataset comprises 300 underwater images and serves as a compact benchmark for assessing performance across various controlled scenarios. The UIQS dataset includes 3,630 images, offering a wide range of underwater conditions such as varying levels of turbidity, lighting, and object clarity, making it ideal for large-scale evaluation. To further validate our method's robustness and real-world applicability, we also employ the UIEB dataset, which contains 890 raw underwater images captured under natural conditions with diverse depths, haze levels, and color distortions. Together, these datasets enable a comprehensive assessment of our approach across both controlled and challenging real-world scenarios.

EVALUATION METRICS

1. Edge Intensity (EI)
    - Measures sharpness of edges. Higher EI means better preservation of edges and fine details.

$$\mathrm{EI} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} |\nabla I(x, y)|$$

Where $\nabla I(x, y)$ is the gradient magnitude at pixel (x, y).

EVALUATION METRICS

2.Average Gradient (AG)

- Indicates the overall sharpness and edge clarity in the image.
- Higher values = more detail and clearer boundaries.

$$\mathrm{AG} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} \sqrt{G_x^2(x,y) + G_y^2(x,y)}$$

Where:

- G_x, G_y = image gradients using Sobel operator in x and y directions

EVALUATION METRICS

3.Information Entropy (IE)

Indicates image information richness. Higher IE means more detail and better contrast distribution.

$$\mathrm{IE} = -\sum_{i=0}^{L-1} p_i \log_2(p_i)$$

Where p_i is the probability of pixel intensity i, and L is the number of gray levels.

EVALUATION METRICS

4.Colorfulness Contrast Fog Density Index (CCF)
Assesses color vibrancy and contrast. Higher CCF reflects better visibility and color restoration.

$$\mathrm{CCF} = \sigma_{rg} + 0.3 \cdot \mu_{rg} + \sigma_{yb} + 0.3 \cdot \mu_{yb}$$

Where $rg = R - G$, $yb = 0.5(R + G) - B$, μ and σ are the mean and standard deviation.

CHALLENGES FACED

SEVERE COLOR DISTORTION

Underwater images often suffer from significant loss of red light and excessive blue/green dominance due to light absorption, making color restoration complex.

NON-UNIFORM LIGHTING AND HAZE

Scattering and absorption cause strong haze and uneven illumination, especially at greater depths, making traditional enhancement methods less effective.

LACK OF GROUND TRUTH

Unlike other domains, there is no "perfect" reference image for underwater scenes, making supervised learning and objective evaluation difficult.

HIGH VARIABILITY IN IMAGE CONDITIONS

Images vary greatly in depth, water type, turbidity, and lighting, requiring methods that generalize well across diverse scenes (like in UIEB and U45).

CHALLENGES FACED

ARTIFACTS INTRODUCED BY ENHANCEMENT
Over-enhancement can lead to unnatural colors, excessive sharpness, or halo artifacts, reducing visual quality instead of improving it.

EVALUATION METRIC LIMITATIONS
Common metrics may not fully capture subjective visual quality; thus, choosing or designing effective metrics (like entropy, IEI, colorfulness) is crucial.

COMPUTATIONAL COMPLEXITY
Some advanced enhancement techniques (like fusion-based or deep learning models) are computationally expensive, limiting their use in real-time applications.

QUANTITATIVE ANALYSIS OF ENHANCEMENT RESULTS

METRIC	ORIGINAL IMAGE	ENHANCED IMAGE	REMARKS
Color Saturation (Mean)	99.24	112.16	Richer colors; makes image visually appealing
Contrast	31.79	39.92	Better separation between light and dark areas
Entropy (Grayscale)	6.93	7.30	More detail and texture captured in image
White Balance (A, B)	A=100.8, B=141.9	A=115.0, B=136.4	Color tones shift toward neutral (natural look)
Edge Sharpness	9.25	12.46	Crisper edges; objects more defined and clear

*UIEB dataset

CONCLUSION

In conclusion, the image enhancement process significantly improved the visual quality of the image using a combination of several techniques.We started with White Balance Correction, which effectively removed any color imbalances and ensured the colors appeared more natural and balanced. Next, Image Decomposition was applied, separating the foreground and background to emphasize key elements, enhancing clarity and focus on the subject matter. Percentile Maximum Contrast Enhancement further improved the image by adjusting the contrast based on pixel intensity percentiles, bringing out more details and enhancing the overall dynamic range. Image Fusion was used to combine features from multiple images based on entropy, ensuring that important details from each image were preserved and merged to improve sharpness and clarity. These methods, when applied together, not only improved contrast, sharpness, and color balance but also resulted in an overall image that was visually striking, with more defined details, better clarity, and a more natural color representation.

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THANK YOU