Underwater Image Restoration Through a Prior Guided Hybrid Sense Approach and Extensive Benchmark Analysis

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1. Introduction / Abstract

Core Problem: Taking pictures underwater is difficult. Light behaves differently in water than in air, causing images to look blurry and have a strong blue or green color cast. This is because water absorbs red light much faster than blue or green light. This poor image quality makes it hard to use underwater photos for important tasks like studying marine ecosystems, exploring shipwrecks, or inspecting underwater equipment.

Proposed Solution & Main Finding: To solve this, researchers developed a new Artificial Intelligence (AI) model called **GuidedHybSensUIR**. This model uses a "hybrid" approach, combining two powerful AI techniques: 1. **Convolutional Neural Networks (CNNs)** (AI models that process images by applying filters to find local patterns) to restore fine, blurry details. 2. **Transformers** (AI models that are excellent at understanding the overall context and relationships across an entire image) to fix the global color problems.

The key innovation is a new guiding principle called the **Color Balance Prior**. This is based on the simple idea that in a normal, well-lit photo, the average of all the red, green, and blue color values should be roughly equal (resulting in a neutral gray). The model uses this "prior" as a target to guide its color correction process. The researchers also created a comprehensive benchmark by collecting thousands of images from four different real-world datasets and testing 37 existing methods to create a fair standard for comparison. Their proposed method outperformed all of them in overall testing.

Limitations: While the proposed method performed best overall across a wide range of tests, the paper notes that it did not achieve the absolute best score in every single individual test case when compared to all 37 other methods.

2. Methodology

The researchers followed a systematic, three-step process to develop and validate their model.

1. **Establish a Standard Benchmark:** The team first noticed that different researchers were using different datasets to test their models, making it impossible to know which method was truly better. To fix this, they created a large, standardized benchmark. They gathered over 5,600 training images and nearly 1,000 test images from four diverse, real-world underwater datasets. They then retrained and tested 37 existing methods on

this benchmark to create a fair and reliable comparison.

2. **Design a Hybrid AI Architecture:** They designed their AI model, GuidedHybSensUIR, using a popular U-shaped structure that is good at processing images at multiple scales.
   - **The "Down" Path (Encoder):** The model first analyzes the distorted image. It uses modules called **Detail Restorers**, which are based on **CNNs**, to capture and fix small, blurry details at progressively coarser scales.
   - **The "Bottom" (Bottleneck):** At the coarsest level, where the model sees the "big picture," a module called the **Feature Contextualizer** takes over. This module, built with **Transformers**, focuses on fixing the overall color by analyzing the relationships between the color channels across the entire image.
   - **The "Up" Path (Decoder):** The model then reconstructs the clear image. It combines the global color information from the bottleneck with the fine-detail information saved from the encoder path. Special modules called **Scale Harmonizers** are used to seamlessly blend these different layers of information together.
3. **Integrate the Color Guide:** The **Color Balance Prior** is calculated for each input image and fed into the AI. It acts as a strong guide in the Feature Contextualizer to steer the global color correction and as a weaker, final "reminder" in the decoder to ensure the final output looks natural and balanced.

3. Theory / Mathematics

The two most important theoretical concepts are the Color Balance Prior and the composite loss function used to train the model.

1. The Color Balance Prior

This concept is inspired by the "Gray World Assumption," which states that for an image with a wide variety of colors, the average of the red, green, and blue components should average out to a shade of gray. The researchers use this to create a guide for their AI.

The formula for the prior is:

$$Priori(x, y) = \frac{R(x, y) + G(x, y) + B(x, y)}{3}$$

What it means: For every single pixel in the image (at location *x, y*), this formula calculates the average value of its red (R), green (G), and blue (B) channels. This average value is then used to create a new "prior" image where the red, green, and blue channels are all set to this same average value. The result is essentially a grayscale image that represents a perfectly color-balanced target. The AI uses this "prior" image as a map to learn how to adjust the colors in the distorted underwater photo to make them look more natural, as if they were taken in air.

2. The Composite Loss Function

The "loss function" is a scoring system that tells the AI how well it's doing during training. The goal is to minimize this score. The researchers combined three different scores to evaluate the restored image from multiple perspectives.

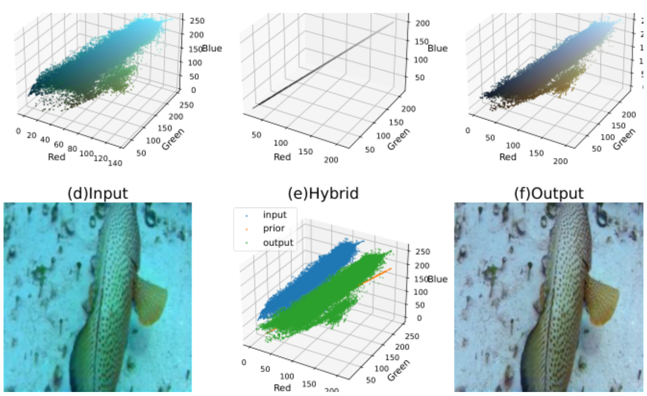
The formula is:

$$L = w_1 \cdot L_f + w_2 \cdot L_s + w_3 \cdot L_p$$

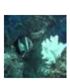
What it means: The total error score (L) is a weighted sum of three different types of error: * L_f (**Fidelity Loss**): Measures the pixel-by-pixel difference between the AI's output and the perfect reference image. This ensures the colors are accurate. * L_s (**Structural Loss**): Measures the similarity in structure, contrast, and brightness. This ensures the image's composition looks right. * L_p (**Perceptual Loss**): Uses another pre-trained AI to judge whether the restored image *looks* good to a human. This focuses on realistic textures and overall visual appeal.

By trying to minimize this combined score, the AI learns to produce images that are not only technically accurate but also visually pleasing.

4. Key Diagrams or Visual Elements



- **Figure 1:** This figure uses 3D scatter plots to show why the **Color Balance Prior** works. The plot for the input image shows all the colors clustered in the blue-green corner. The plot for the prior is a perfect diagonal line (representing gray). The plot for the final restored image shows the colors are now spread out evenly and centered around that diagonal line, visually proving that the prior successfully guided the color correction.


- **Figure 2:** This is the master blueprint of the entire AI model. It clearly shows the U-shaped architecture, with the **Detail Restorer** modules in the encoder (left side), the **Feature Contextualizer** at the bottom, and the

Scale Harmonizer modules in the decoder (right side). It also illustrates how the Color Balance Prior is fed into the model to guide the process.

- **Figure 5:** This diagram provides a closer look at the **Feature Contextualizer**, the "brain" of the color correction process. It shows that this module uses three parallel **Transformer** blocks to analyze the image. Two of these blocks compare the image features to the color prior (cross-attention), while the third analyzes the image's own internal features (self-attention). The results are then fused using **quaternion convolution** (a mathematical operation that helps combine different streams of information in a structured and efficient way).

- **Table I:** This table contains the main numerical results of the study. It compares the researchers' model ("Ours") against 37 other methods on three different test datasets. It uses standard image quality metrics like PSNR (measures pixel accuracy) and SSIM (measures structural similarity). The table clearly shows that the proposed method achieves the highest or second-highest scores in nearly every category, providing strong quantitative evidence of its superiority.
- **Figures 9, 10, & 11:** These figures provide the visual proof. They show side-by-side comparisons of distorted underwater images restored by various methods. In these examples, the images produced by the researchers' model are visibly clearer, have more accurate and vibrant colors, and show finer details than the images produced by competing state-of-the-art methods.

5. Conclusion

The researchers successfully created a new AI framework, **GuidedHybSensUIR**, that significantly improves the quality of underwater images. The model's strength comes from its hybrid design, which uses **CNNs** to fix fine details and **Transformers** to correct overall color, all guided by an innovative **Color Balance Prior**. By creating a new, comprehensive benchmark dataset and outperforming 37 other state-of-the-art methods, this work sets a new standard in the field.

Why It Matters: This research provides a powerful tool that can help us see the underwater world with unprecedented clarity. This can accelerate scientific discovery in marine biology, improve the safety and efficiency of inspecting underwater infrastructure like bridges and pipelines, and allow filmmakers and photographers to capture the true beauty of our oceans.