Underwater Image Restoration Through a Prior Guided Hybrid Sense Approach and Extensive Benchmark Analysis
Summarized on August 3, 2025

1. **Introduction / Abstract**
   The paper addresses the problem of underwater images suffering from color distortions (mainly blue or green hues) and blurriness caused by light absorption and scattering in water. These issues degrade image quality and hinder tasks like marine life segmentation and object recognition. The authors propose a novel underwater image restoration (UIR) framework called GuidedHybSensUIR, which combines multi-scale processing with a new Color Balance Prior (a simple average of RGB channels to guide color correction). Their method uses a hybrid of convolutional neural networks (**CNNs**, which extract local image features) and Transformers (which capture long-range dependencies) to restore both fine details and overall color balance. They also create a comprehensive benchmark dataset from multiple real-world underwater image datasets and evaluate 37 existing methods, showing that their approach outperforms state-of-the-art techniques overall.

2. **Methodology**
   The researchers designed a U-shaped neural network architecture with three main components:

- **Detail Restorer:** Uses CNNs with quaternion convolutions (a mathematical way to represent RGB channels jointly) to recover fine, local image details at multiple scales. It integrates two blocks: Residual Context Block (RCB) for capturing contextual information and Nonlinear Activation-Free Block (NAFB) for efficient feature processing.

- **Feature Contextualizer:** A Transformer-based module at the network bottleneck that models global color relationships using three types of attention mechanisms—Adjust Color Transformer (ACT), Keep Feature Transformer (KFT), and Self-Attention Transformer (SAT). These focus on cross-attention between image features and the Color Balance Prior, and self-attention within image features themselves. The attention is computed across feature channels rather than image patches to reduce computational cost.

- **Scale Harmonizer:** In the decoder, this module fuses multi-scale features from the encoder and bottleneck, using learnable scaling and shifting parameters to harmonize feature amplitudes for better reconstruction.

The Color Balance Prior, inspired by the Gray World Assumption (which expects average RGB values to be equal in natural lighting), is used as a strong guide in the Feature Contextualizer and a weak guide in the final decoding stage to steer color correction.

3. **Theory / Mathematics**
   The Color Balance Prior is mathematically derived from the relationship between observed pixel intensity $f_i(x, y)$ in channel i (R, G, or B), scene geometry $G(x, y)$, object reflectance $R_i(x, y)$, and illumination $I_i(x, y)$:

$$f_i(x, y) = G(x, y)R_i(x, y)I_i(x, y)$$

   Assuming constant geometry and reflectance, the average intensity a_i over the image relates to illumination as:

$$a_i \approx I_i \times \text{constant}$$

   In ideal in-air conditions, illuminations are equal across channels:

$$a_R \approx a_G \approx a_B$$

   This forms the basis for the Color Balance Prior, defined as the average of the three RGB channels at each pixel:

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

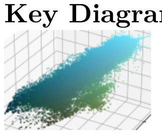
   This prior guides the network to restore balanced color intensities, compensating for underwater wavelength-dependent attenuation.

The attention mechanism in the Feature Contextualizer uses inter-channel cross-attention defined as:

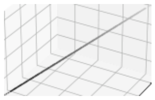
$$\text{InterCAttn}(Q, K, V) = \text{Softmax}\left(\frac{\hat{Q} \cdot \hat{K}^\top}{\tau}\right) \cdot \hat{V}$$

where Q, K, and V are query, key, and value tensors derived from image and prior features, τ is a learnable temperature parameter, and the operation captures relationships between feature channels to adjust color and detail contextually.

4. **Key Diagrams or Visual Elements**



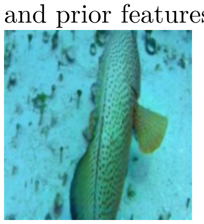
- **Figure 1:** Shows 3D scatter plots of color distributions for an input underwater image, the Color Balance Prior, and the restored output. The prior aligns centrally in the restored image's color distribution, illustrating its effectiveness in guiding color correction.



- **Figure 2:** Depicts the overall GuidedHybSensUIR architecture, highlighting the U-shaped network with Detail Restorer modules in the encoder, the Feature Contextualizer at the bottleneck, and Scale Harmonizers in the decoder.

- **Figure 3 & 4:** Illustrate the internal structure of the Nonlinear Activation-Free Block (NAFB) and the Residual Context Block (RCB), showing how local details and contextual information are processed.

- **Figure 5-7:** Detail the Feature Contextualizer's Multi-Attention Quaternion (MAQ) blocks and the architecture of the Adjust Color Transformer (ACT), explaining how different attention mechanisms operate on image and prior features.



- **Figure 8:** Shows the Scale Harmonizer module, which calibrates multi-scale features during decoding.

- **Tables I-III:** Present quantitative comparisons of the proposed method against 37 other methods on multiple datasets using metrics like PSNR (pixel accuracy), SSIM (structural similarity), LPIPS (perceptual similarity), UCIQE, and UIQM (underwater image quality metrics). The proposed method consistently ranks highest or near highest.

- **Figures 9-11:** Provide visual comparisons showing the proposed method's superior color correction and detail restoration compared to traditional and deep learning methods.

5. **Conclusion**
   The paper presents a novel underwater image restoration framework that effectively combines CNN-based local detail restoration with Transformer-based global color contextualization, guided by a simple but powerful Color Balance Prior. The multi-scale hybrid architecture and attention mechanisms enable superior correction of color distortions and recovery of blurred details. Extensive benchmarking on a newly compiled dataset and comparisons with 37 existing methods demonstrate that this approach outperforms state-of-the-art techniques in both quantitative metrics and visual quality.

Why It Matters: This research advances underwater imaging by providing clearer, more color-accurate images, which are crucial for marine exploration, environmental monitoring, and underwater robotics. The standardized benchmark and open-source code also facilitate future developments in this challenging field.