Supplementary material: Selective Colour Restoration of Underwater Surfaces

BMVC 2022 Submission # 228

Background light estimation

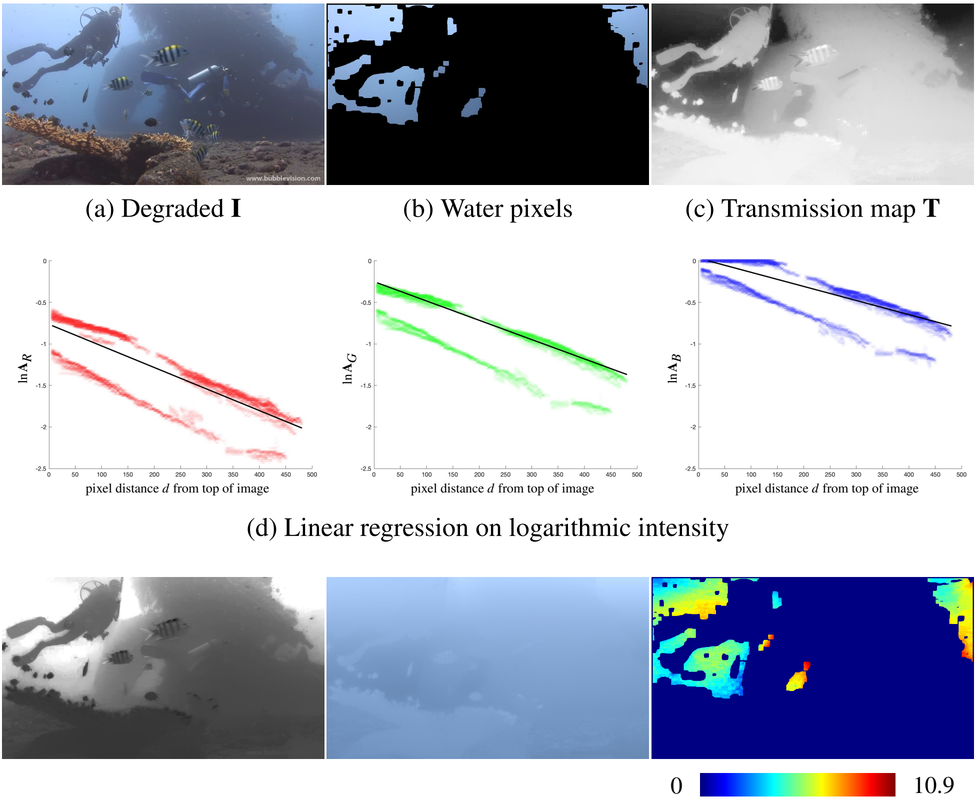
We illustrate the steps of background light estimation (Eqs. 7 to 9 in the manuscript) with an example of non-uniform background light (Fig. 1). The sample image has two main groups of water pixels where the one on the right of the image has darker water colour.

To estimate the intensity change per pixel distance of water pixels, K, we perform linear regression on the logarithmic intensity value against pixel distance (Eq. 7) where K is the slope of the line. Fig. 1(d) visualises the logarithmic intensities against pixel distance of each colour channel. For visualisation purpose, we set the marker transparency such that a more solid colour indicates a higher occurrence of the intensity at the same pixel distance. The two groups of intensity occurrences in each graph corresponds to the two water regions, where the bottom group is from the smaller region in the right of image. We use the MATLAB fitlm() function with robust option to estimate K. Table 1 summarises the results. We note that all the estimated slopes are negative, indicating the water pixel intensity deceases with increasing pixel distances. Moreover, the estimated K for the red colour channel is the most negative, confirming the fact that the red light is most attenuated in oceanic water. The relatively high R^2 for the green colour channel, at 0.979 compared to that of red and blue channels at 0.649 and 0.694, might be due to the fact a colour filter array in the camera has more dense filters for the green colour. We then address the change in water colour for pixels representing surfaces, using the ratio between ranges that is encoded in $\ln \mathbf{T} / \ln \mathbf{T}^{\star}$ (Eq. 8). Using the estimated K and the ratio, we interpolate the non-uniform background light A (Eq. 9).

To validate the proposed estimation, we also measure the colour difference of the water pixels as CIEDE2000 [1]. The average CIEDE2000 difference between estimated background light and the original degraded image the is 6.70, over the valid range of 0 to 100.

Colour channel	Intercept	Slope K	R^2
Red	-0.7639	-0.0026	0.649
Green	-0.2499	-0.0023	0.979
Blue	0.0323	-0.0017	0.694

Table 1: Summary of regression results used to interpolate the non-uniform background light. The negative slopes confirm that the intensity are decreasing along the range. The R^2 value is the proportion (between 0 and 1) of logarithmic intensity that is predictable from the independent variable. The higher R^2 , the better the prediction.



(a) Degraded $\mathbf{I}$ (b) Water pixels (c) Transmission map $\mathbf{T}$

(d) Linear regression on logarithmic intensity

(e) $\frac{\ln \mathbf{T}}{\ln \mathbf{T}^\star}$ (f) Interpolated $\mathbf{A}$ (g) ΔE between $\mathbf{A}, \mathbf{I}$

Figure 1: Proposed non-uniform background light estimation. (a-c) The degraded image I, identified water pixel and estimated transmission map. (d) We perform linear regression on natural logarithm intensity to estimate the intensity change per pixel distance for each colour channel. For visualisation purpose, we set the transparency of each marker to 0.01 so a more solid colour indicates more pixels have the intensity. (e) Ratio between the range of surfaces $\frac{\ln \mathbf{T}}{\ln \mathbf{T}^\star}$. (f) Estimated non-uniform background light A using the linear regression results (Eq. 9). (g) Colour difference of water pixels between A and I, measured as CIEDE2000 ΔE. The lower the value, the more perceptually similar the two colours are.

References

[1] G. Sharma, W. Wu, and E. Dalal. The CIEDE2000 color-difference formula: Implementation notes, supplementary test data, and mathematical observations. *Color Research & Application*, 30(1):21–30, Dec. 2005.