CIS centre for intelligent sensing

1. Introduction

- Existing methods



2. SeCA (cont.) **Residual colour-cast removal** Underwater images (capture surfaces and water mass) degraded by light attenuation Restore $\hat{\mathbf{J}}$ as if surfaces are under an unattenuated target illuminant ($\rho_t, \gamma_t, \beta_t$), e.g. D65, • Light attenuation depends on distance travelled by light (depth, range) and wavelength with chromatic adaptation [3]: surfaces under large depth are under considerable colour cast $\hat{\mathbf{I}} = \mathcal{M}^{-1} \mathcal{D} \mathcal{M} \mathbf{I}$ - water colour in image could be non-uniform where \mathcal{M} maps the colour into LMS colour space, diagonal matrix \mathcal{D} scales the intensity in each channel to achieve the same cone response mostly addresses degradation along range only & assume uniform water colour in image Selectively remove cast from surfaces under (source) attenuated illuminant (ρ_s , γ_s , β_s) - few methods remove colour cast along depth but also distort water colour $\mathcal{D} = \operatorname{diag}((\rho_t/\rho_s)^{\eta}, (\gamma_t/\gamma_s)^{\eta}, (\beta_t/\beta_s)^{\eta}), \eta \in [0, 1]$ • Goal: restores colour as if surfaces are captured in air & maintain water colour Control cast removal extent of each pixel with η derived from transmission map of **J** surfaces have η values close to 1 (full cast removal) water mass has η values close to 0 (no cast removal) Physics-based method to restore colour in degraded image I along range & depth Estimate attenuated illuminant as $A^{\zeta} \rightarrow$ choose largest ζ with no over-exposure 3. Validation Compared with physics-based & neural networks SeCA shows consistent results in shallow and deep water, and non-uniform water colour Stability demonstrated by direct extension to video Scene adaptive map η Non-uniform $\mathbf{A}, K > 0$ SeCA-restored **Ĵ** Background light estimation Luminance channel of $\hat{\mathbf{I}}$ Repeat with $\zeta \in [1,0.95,...,0]$ Residual cast removal Video & Code Range-compensated image J appears as if no water between surface and camera SeCA Ucolor [5] UWHL [4] Degraded $\mathbf{I} = \mathbf{T} \cdot \mathbf{J} + (\mathbf{1} - \mathbf{T}) \cdot \mathbf{A}$ with *to-be-estimated* transmission map $\mathbf{T} = e^{-\beta z} \in [0, 1]$ and background (ambient) light **A** 4. Conclusion SeCA addressed two issues in state-of-the-art non-uniform water colour in restoration along range estimate T_R from Red Channel Prior [2] removal of residual colour cast from surfaces without distorting the water colour - obtain $\mathbf{T}_k = (\mathbf{T}_R)^{\beta_k/\beta_R}, k \in \{G, B\}$ SeCA demonstrated how combining oceanic domain knowledge and image processing technique could outperform neural network, when ideal training data is scarce - Derive colour ratio constraint to identify water pixels Reference \rightarrow representative water colour A^* at pixel location (x^{*}, y^{*}) [1] Schechner and Karpel, 'Clear underwater vision', CVPR 2004

- Address wavelength-dependency of **T**
- A represents the water mass i.e. water colour

 - interpolating as

$$\mathbf{A}(\mathbf{x},\mathbf{y}) = \mathbf{A}^* \exp\left(-\frac{1}{2}\right)$$

 \rightarrow Also handles uniform **A** (when K = 0)

SELECTIVE COLOUR RESTORATION OF UNDERWATER SURFACES

Chau Yi Li, Andrea Cavallaro chauyi.li@qmul.ac.uk, a.cavallaro@qmul.ac.uk

Address non-uniform A by estimating attenuation coefficient per pixel distance K and

 $\mathbf{A}(\mathbf{x},\mathbf{y}) = \mathbf{A}^* \exp\left(-\frac{\ln \mathbf{T}}{\ln \mathbf{T}^*}K(y-y^*)\right)$



[2] Galdran et al., 'Automatic Red-Channel underwater image restoration', JVCIR 2015 [3] Gijsenij, et al., 'Computational color constancy: Survey and experiments', TIP 2011 [4] Berman et al., 'Underwater Single Image Color Restoration Using Haze-Lines and a New Quantitative Dataset', PAMI 2021

[5] Li et al., 'Underwater image enhancement via medium transmission-guided multi-color space embedding', TIP 2021





Paper ID 228

