Background light estimation for depth-dependent underwater image restoration

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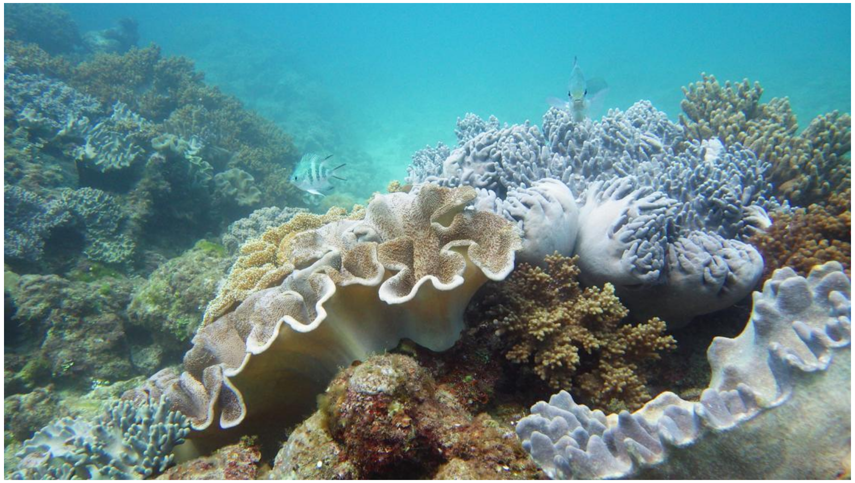
Underwater image degradation



- By light attenuation in water
  - Absorption
    → reduced intensity
  - Scattering
    → blurred image
- Wavelength-dependent
  - More observable for red light in open ocean water
    → blue/ green colour cast

Light attenuation

- Quantified by attenuation coefficient β
- Dependent on the distance travelled d
- Follows Beer-Lambert Law [1]

$$portion\ of\ remaining\ intensity = e^{-\beta d}$$

[1] Swinehart, “The beer-lambert law,” J. Chem. Educ., 1962.

Image formation model [2]

Underwater image

$$I(x,y) = t(x,y)\,J(x,y) + (1 - t(x,y))\,A(x,y)$$

Transmission map

- modulates $J(x,y)$
- depends on
  - *scene-to-camera distance* $d(x,y)$
  - water types β: $t(x,y) = e^{-\beta d(x,y)}$ [1]

Scene irradiance

- non-attenuated propagation path to camera
- to be recovered

Background light

- veiling effect
- often assumed to be constant global background light A

[1] Swinehart, "The beer-lambert law," J. Chem. Educ., 1962.
[2] Schechner and Karpel, "Clear underwater vision," in CVPR, 2004.

Recovering $J(x, y)$

- Remove the effect of degradation along scene-to-camera distance

$$J(x, y) = \frac{I(x, y) - A(x, y)}{t(x, y)} + A(x, y)$$

- Requires estimation of $t(x, y)$ and $A(x, y)$

- Restored image
  - As if taken directly in front of camera
  - No change to water colour

Constraints for A estimation

- Selected from water region
  - Blue or green colour → *ratio constraint*
  - Flat region → *variance constraint*

- Ratio constraint → pixel-wise
  - $\because \beta^g < \beta^r$ and $\beta^b < \beta^r$
  - From [3] $\frac{\beta^c}{\beta^r} = \frac{b^c A^r}{b^r A^c} < 1$
  - $A^r < 0.9109 A^g$ and $A^r < 0.9109 A^b$

- variance constraint → patch-wise
  - $V(x, y)$: variance of patch centred at pixel (x, y)
  - $V(x, y) < \zeta^2$

[3] Zhao et. al, "Deriving inherent optical properties from background color and underwater image enhancement," in J. Ocean Eng., 2015.

Example of constraint candidates for A

$I(x, y)$

ratio constraint candidates

variance constraint candidates

Combining constraints for A

- Candidate region: region proposals [4] with >50% fulfilling both constraints

$I(x, y)$

candidate regions

Select A at

$$(x^*, y^*) = \max_{(x,y)\in I} \underbrace{\max\left(I^g(x,y), I^b(x,y)\right)}_{\text{dominating colour}} - \underbrace{I^r(x,y)}_{\text{most attenuated}}$$

dominating colour

most attenuated

[4] Pont-Tuset et. al, "Multiscale combinatorial grouping for image segmentation and object proposal generation," in IEEE Trans. Pattern Anal. Mach. Intell., 2017.

More about $A(x, y)$

- Not constant for
  - Water types with large β
  - Capturing large vertical depth
  - Taken near water surface
- Incorrect estimation $\rightarrow$ distorted water colour

$I(x, y)$

$J(x, y)$ with constant A

$A(x, y)$ estimation

- Unknown β and depth range
  - Assumed to be known in [5]
  - Information not always available

- Proposed method:
  estimate change in $A(x, y)$ *without* additional information

[5] J. Chiang, Y. Chen, and Y. Chen, “Underwater image enhancement: Using wavelength compensation and image dehazing,” in IEEE TIP, 2012.

$A(x,y)$ estimation - proposed

- $\hat{\beta}$: attenuation coefficient *per pixel distance* for water
- A_0 : intensity at top of image
- For each pixel at pixel distance $D(x,y)$ from top:

$$\mathrm{A}(x,y) = A_0 e^{-\hat{\beta} D(x,y)}$$

$$\ln A(x,y) = \ln A_0 - \hat{\beta} D(x,y)$$

Linear regression to obtain A_0 and $\hat{\beta}$

$A(x, y)$ estimation - proposed

- Linear regression with L_1 error
- From the connected component containing A
- Interpolate using $\hat{\beta}$ to obtain $A(x, y)$
  - $\hat{\beta} = 0$ reduces $A(x, y)$ to A

$J(x,y)$ with constant A

$J(x, y)$ with $A(x, y)$

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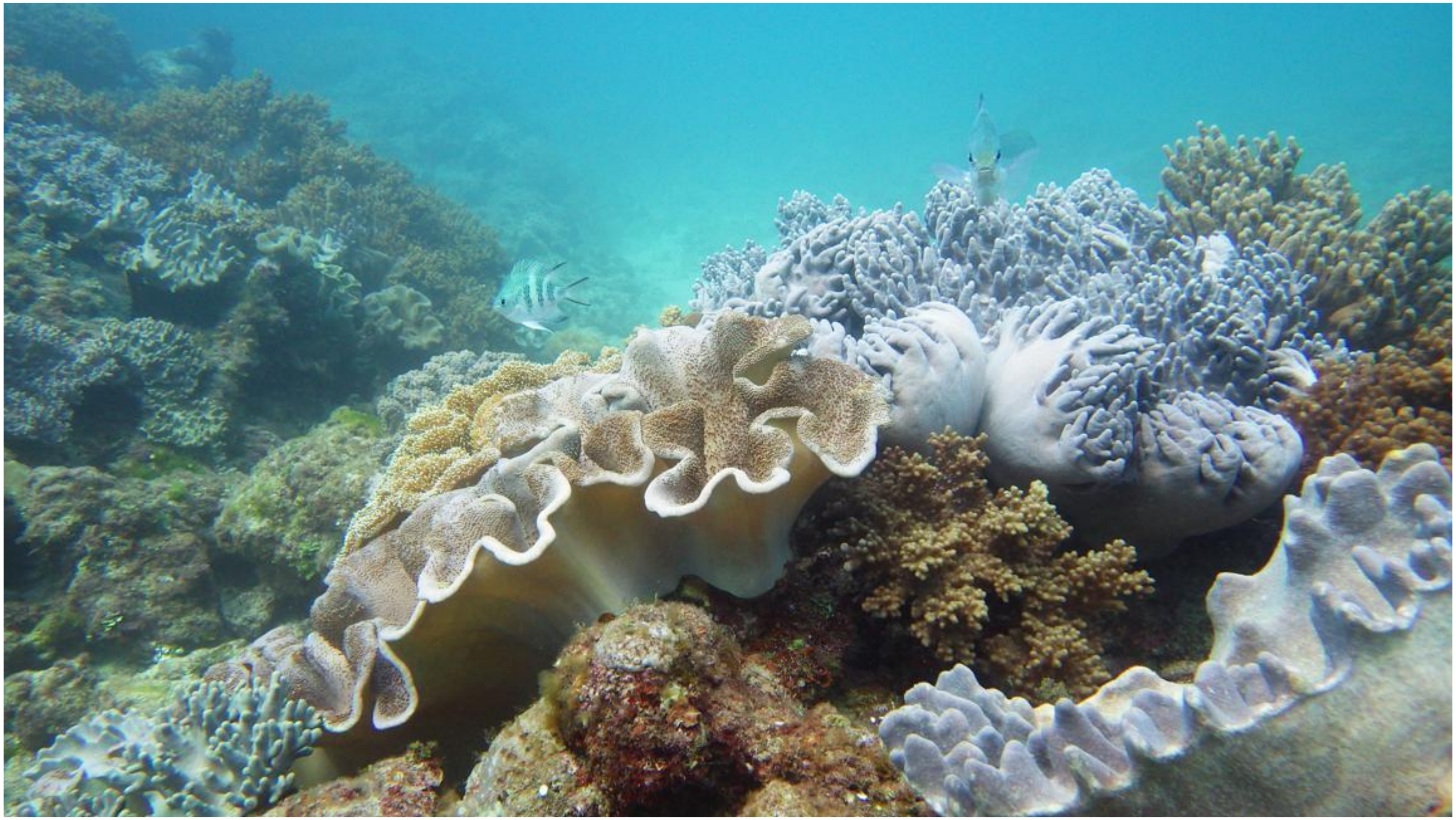
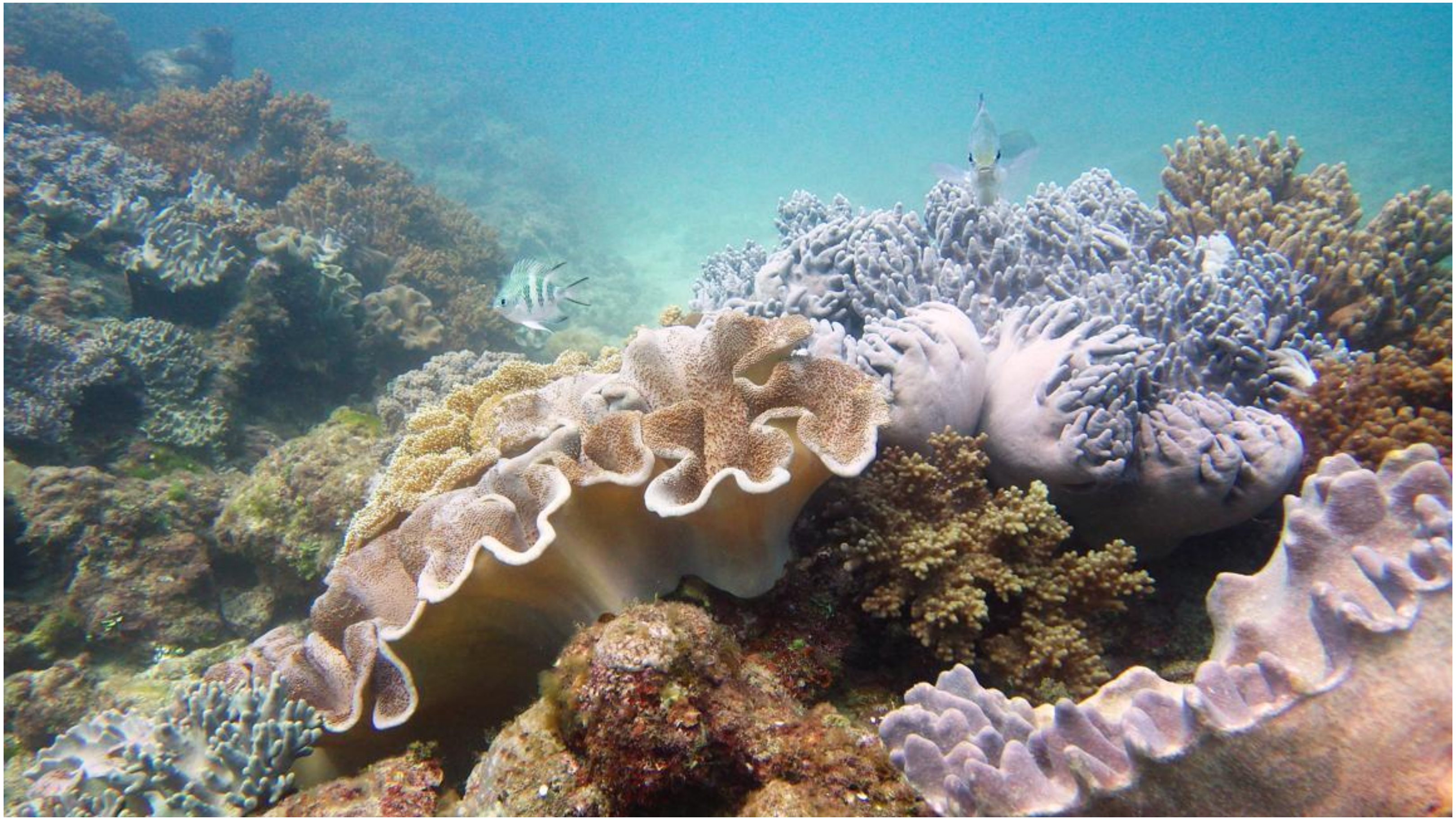
$I(x, y)$



$J(x, y)$



$I(x, y)$

$J(x, y)$

$I(x, y)$

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$J(x, y)$

Evaluation

- No ground truth available
- Compared with 4 restoration methods on 60 images

- Quantitative
  - Preservation of water colour
  - Water region segmented manually with [6]
  - Quantified by MSE and PSNR

- Subjective experiment
  - Online evaluation form
  - ’select the most attractive image’ out of original and 5 methods
  - Each image evaluated 20.25 times

[6] Russell et. al “LabelMe: a database and web-based tool for image annotation,” Int. J. Comput. Vis., 2008.

Evaluation result

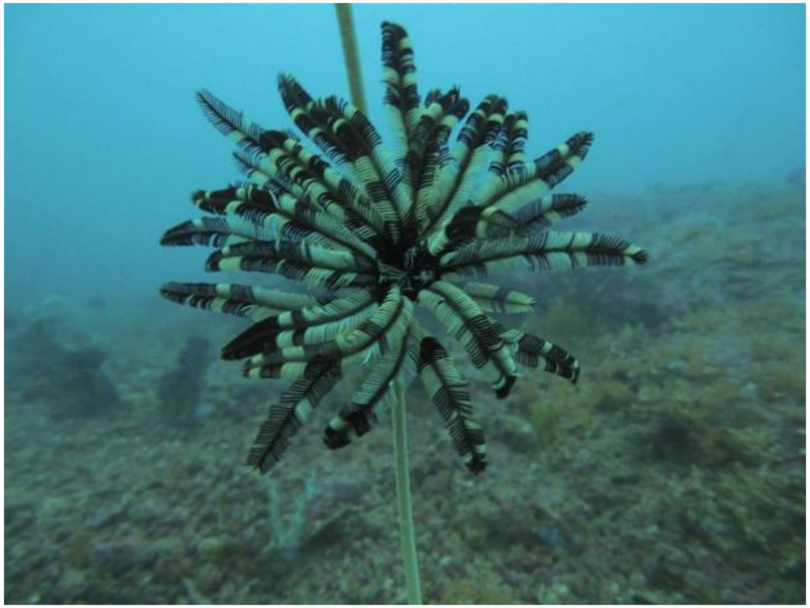
	Org.	DCP	ARC	WCID	BLA	*Pro*
$MSE_c \downarrow$	N/A	.0440	.0156	.0190	.0112	.0014
$PSNR_l \uparrow$	N/A	21.5	25.2	27.9	29.3	37.0
avg (%) $\uparrow$	9.9	15.8	9.5	16.9	30.9	16.9
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

- Lowest error for water colour preservation
- Subjective evaluation result
  - Underperform to method with contrast adjustment (BLA [7])
  - Design of evaluation

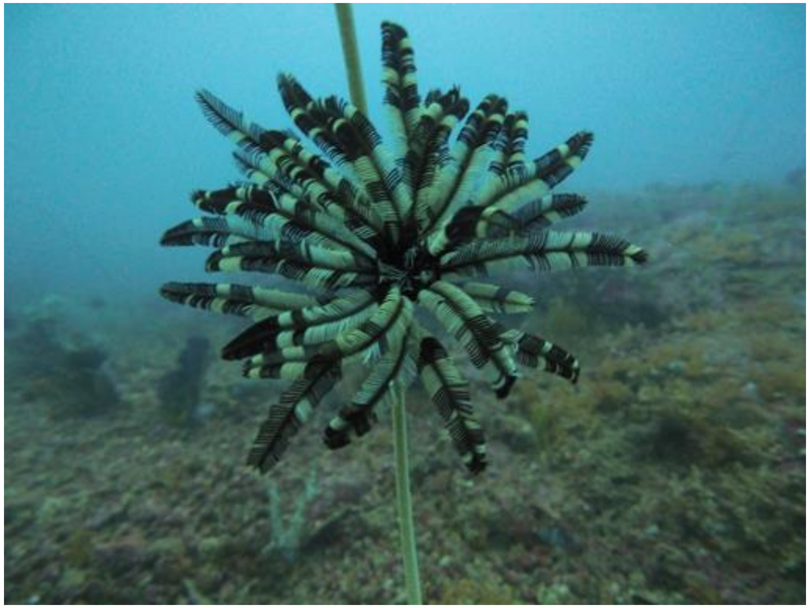
[7] Peng and Cosman, "Underwater image restoration based on image blurriness and light absorption," in IEEE Trans. Image Process., 2017.

Limitation

- Limited improvement over images of small red intensity
- Does not account for degradation along vertical depth



$I(x, y)$



$J(x, y)$

Conclusion and future work

We proposed:

- Physical model based selection of A
- Estimation of $A(x, y)$ *without* prior knowledge of the scene

Future work:

- Compensation for degradation introduced by vertical depth