Mosaicing Deep Underwater Imagery

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Introduction and motivation

- Given a set of deep underwater images, this framework performs two tasks: **Underwater Image Restoration** and **Depth-based Image Stitching**.
- **Challenges**: Non-uniform illumination, presence of haze, significant parallax effects across images.
- **High level idea**: Depth estimate obtained via dehazing can be employed to perform depth-aware stitching.
- **Solution**:
  - Channel-wise gradient prior for illumination compensation.
  - Depth-aware spatially varying homography for image alignment.

Non-uniform Illumination correction

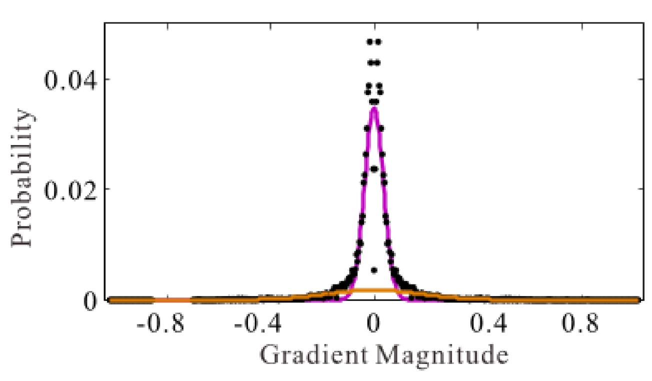


Figure 1: Natural image gradients

- $z(x) = i(x)m(x)$, z - non-uniformly illuminated image, i - uniformly illuminated image, m - illumination map.
- We use a MAP formulation to solve for m

- Objective function is formed by enforcing
  - Smoothly varying bivariate polynomial prior on M

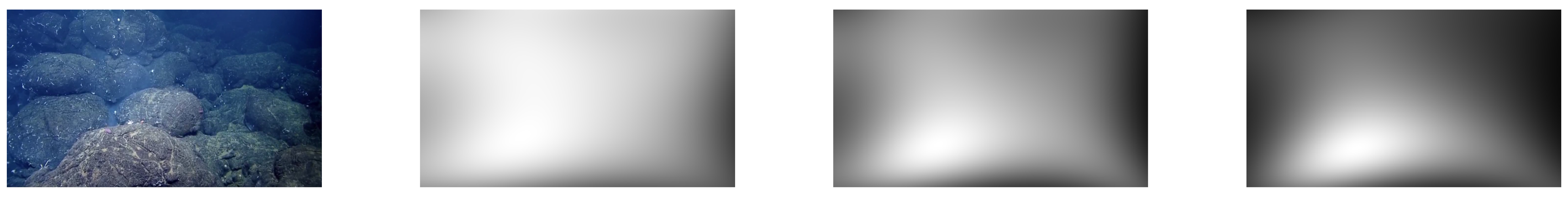
$$M(x) = \sum_{t=0}^{D}\sum_{l=0}^{t} a_{t-l,l}\, p^{t-l}(x) q^{l}(x) \quad (1)$$

  - Sparsity prior on the image gradients:

$$O = \sum_{(i,j)} |\psi^{Z}(x) - \psi^{M}(x)|^{\alpha} + \sum_{t=0}^{D}\sum_{l=0}^{t} a_{t-l,l} \quad (2)$$

where, ψ - Gradient operator, $\alpha < 1$, $M = \log(m)$, $Z = \log(z)$

- We solve for M by minimizing O using iteratively re-weighted least squares.



(a) Original Image (b) blue (c) green (d) red

Figure 2: Illumination map differences due to wavelength dependent scattering.

Deep Underwater Haze model

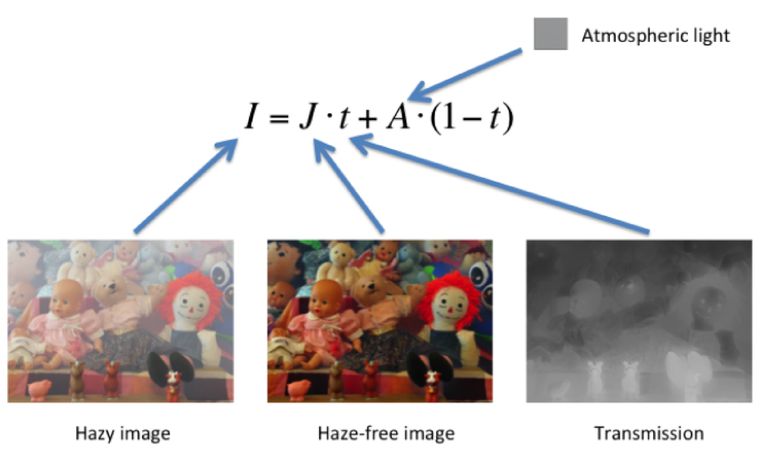


Figure 3: Atmospheric Haze model

$$I(x) = E_d(x) + E_b(x) \quad (3)$$

$$E_d(s,\lambda) = J(\lambda)\exp(-2s\alpha(\lambda)) \quad (4)$$

$$E_b(s,\lambda) = A(\lambda)(1 - \exp(-2s\alpha(\lambda))) \quad (5)$$

Dehazing using Red-channel DCP

- Transmission map (t) is estimated using Red-channel DCP [1]

$$t(x) \;=\; 1 - \min\left(\frac{\min_{y\in\omega}(1 - I^{R}(y))}{1 - A^{R}}, \frac{\min_{y\in\omega}(I^{G}(y))}{A^{G}}, \frac{\min_{y\in\omega}(I^{B}(y))}{A^{B}}\right) \quad (6)$$

- Relative depth map is obtained as $D(x) = -\log(t(x))$
- Final image restoration:

$$J^{c}(x) = \frac{(I^{c}(x) - A^{c})}{\max(t(x), t_0)} + (1 - A^{c})A^{c} \quad (7)$$

(a) (b) (c)

Figure 4: (a) Hazy image, (b) restored image, and (c) depth-map obtained.

Depth-aware Stitching Algorithm

- Let $\mathbf{x} = [x\ y]^{T}$ and $\mathbf{x}' = [x'\ y']^{T}$ be the location of matching points across overlapping images I and I'.
- We use a set of spatially varying homographies to form correspondences across images. A local homography $\hat{h}_*$ at '$*$' is estimated as

$$\hat{h}_* = \arg\min_{h} \sum_{i=1}^{N} \|w_*^{i} a_i h\|^2 \;\; \text{s.t} \;\; \|h\| = 1 \quad (8)$$

$$w_*^{i} = \exp\left(-\frac{\|d_* - d_i\|^2}{\sigma^2}\right) \quad (9)$$

a_i - is a 2×9 matrix formed from the coordinates $\mathbf{x}_i$ and $\mathbf{x}'_i$ of i^{th} point correspondence, d_i - depth at i, N - total number of point correspondences.

(g) (h) (i)

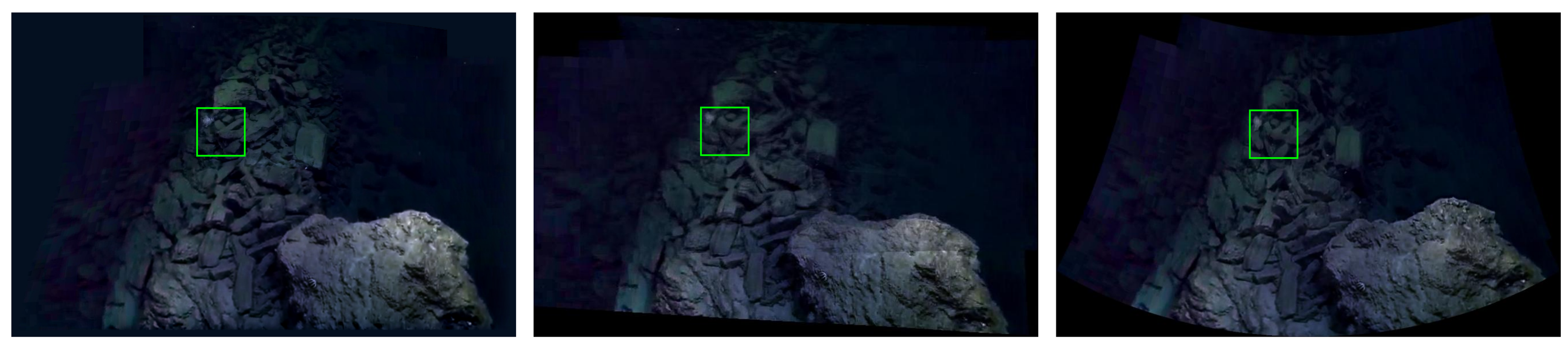
(g) (h) (i)

Figure 5: (a-c) Restored forms of input images. (d-f) Aligned images using the proposed local homography warps.

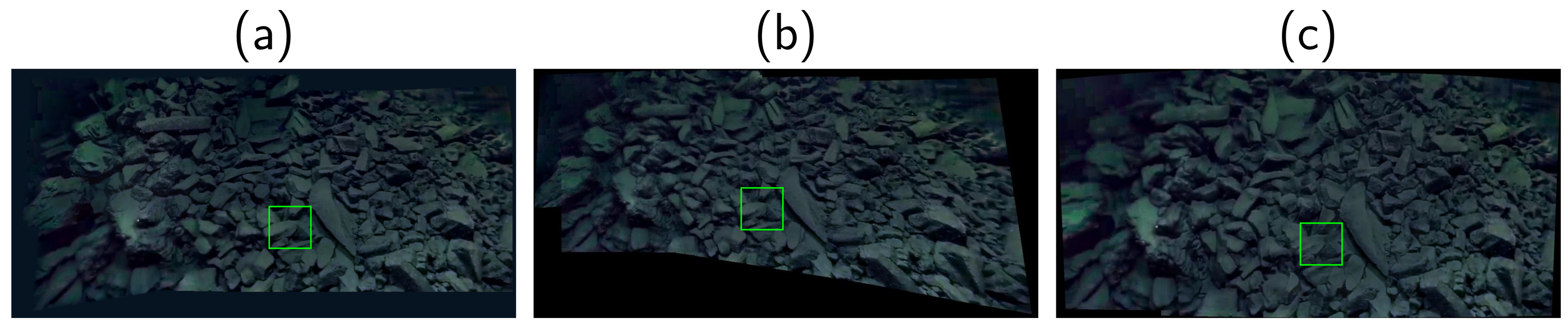
Results

(a) (b) (c)

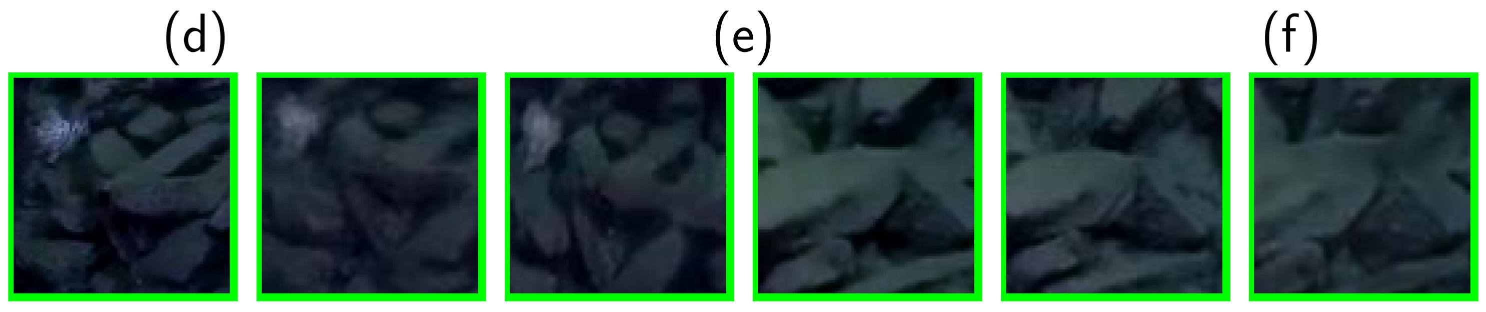
Figure 6: Mosaics obtained using (a) proposed method, (b) APAP [2], and (c) AutoStitch [3] respectively show superior performance of our method in overlapping regions and regions at different depths.



(a) (b) (c)



(d) (e) (f)



(g) (h) (i) (j) (k) (l)

Figure 7: Mosaics obtained using (a,d) proposed method, (b,e) APAP [2] , and (c,f) AutoStitch [3]. (g-l) Zoomed in patches from a-f.

References

[1] A. Galdran, D. Pardo, A. Picón, and A. Alvarez-Gila, "Automatic red-channel underwater image restoration," *Journal of Visual Communication and Image Representation*, vol. 26, pp. 132–145, 2015.

[2] J. Zaragoza, T.-J. Chin, M. S. Brown, and D. Suter, "As-projective-as-possible image stitching with moving dlt," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2013, pp. 2339–2346.

[3] M. Brown and D. G. Lowe, "Automatic panoramic image stitching using invariant features," *International journal of computer vision*, vol. 74, no. 1, pp. 59–73, 2007.