Visual-Quality-Driven Learning for Underwater Vision Enhancement

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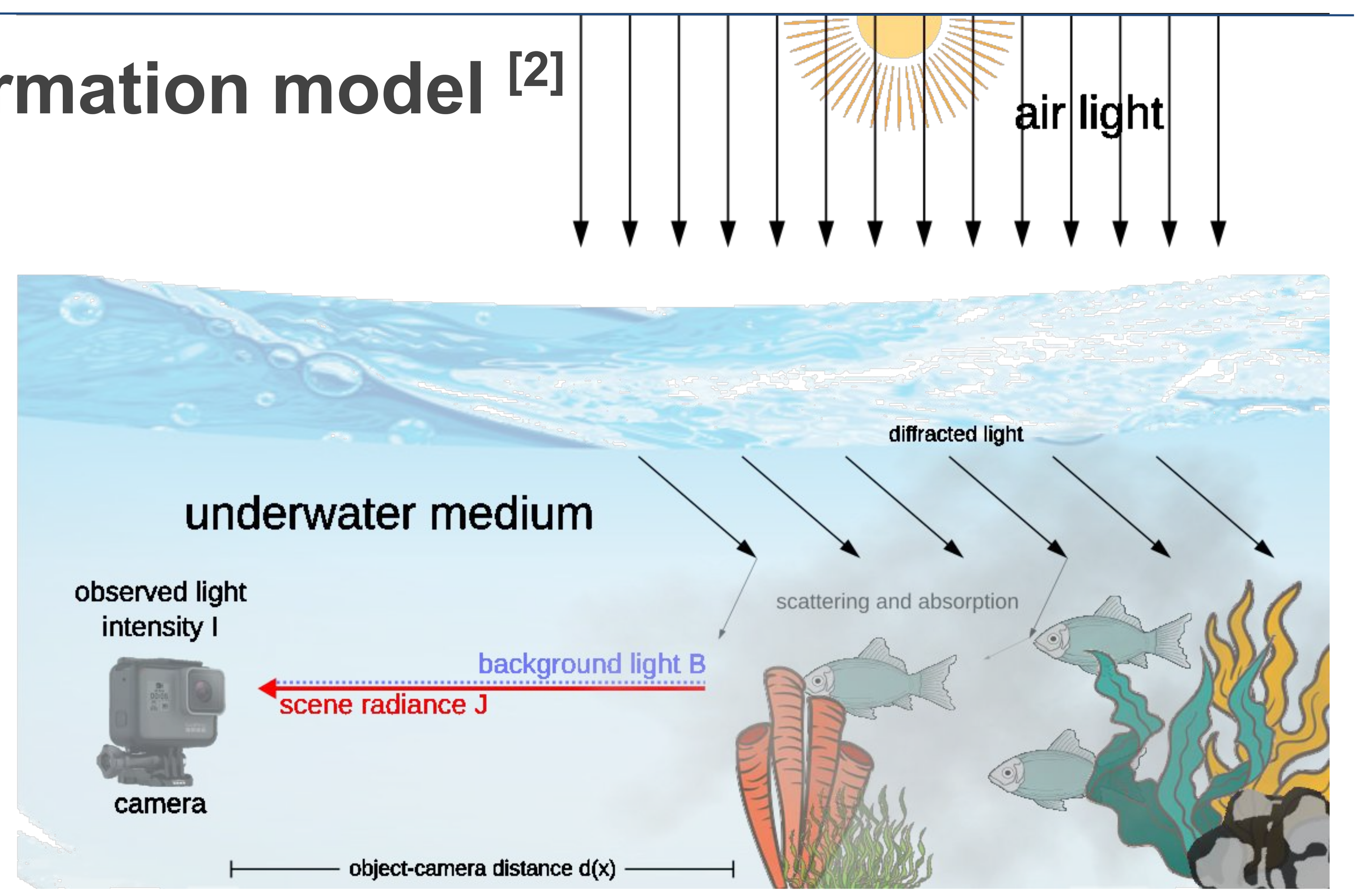
Sum-up

- Enhancement and restoration of images has overcome remarkable advances.
- Due to the complexity of the underwater environment and the lack of ground-truth data, images from this domain remain as a great challenge for the image processing community.
- We formulated a CNN-based approach that uses a set of image quality metrics to guide the restoration learning process.
- Considering the UCIQE metric [1], experiments show that our method improved the visual quality of underwater images.

Image formation model [2]



$J(x) = (I(x) - B)t(x)^{-1} + B$ $\quad B = max_{y \in \{x | t(x) \leq t_0\}} I(y)$

Transmission map estimation

- Supervised training is performed to adjust the selected network to our purpose. It consists in estimating the transmission map of underwater images, comparing such maps to their ground-truths. The transmission map is given by

$$t(x) = e^{-\beta d(x)}.$$

- The loss function used in this stage is the MSE [3], defined as

$$\mathcal{L}_t(I, J) = \frac{1}{n}\sum_{x=1}^{n}(t_I(x) - t_j(x))^2.$$

Visual-quality-driven learning

- To overcome the absence of ground-truth data, we compute a set of Image Quality Metrics (chart below), which we define as

$$IQM(I, J) = \sum_{X \in \mathcal{X}} \lambda_X q_X(I, J),$$

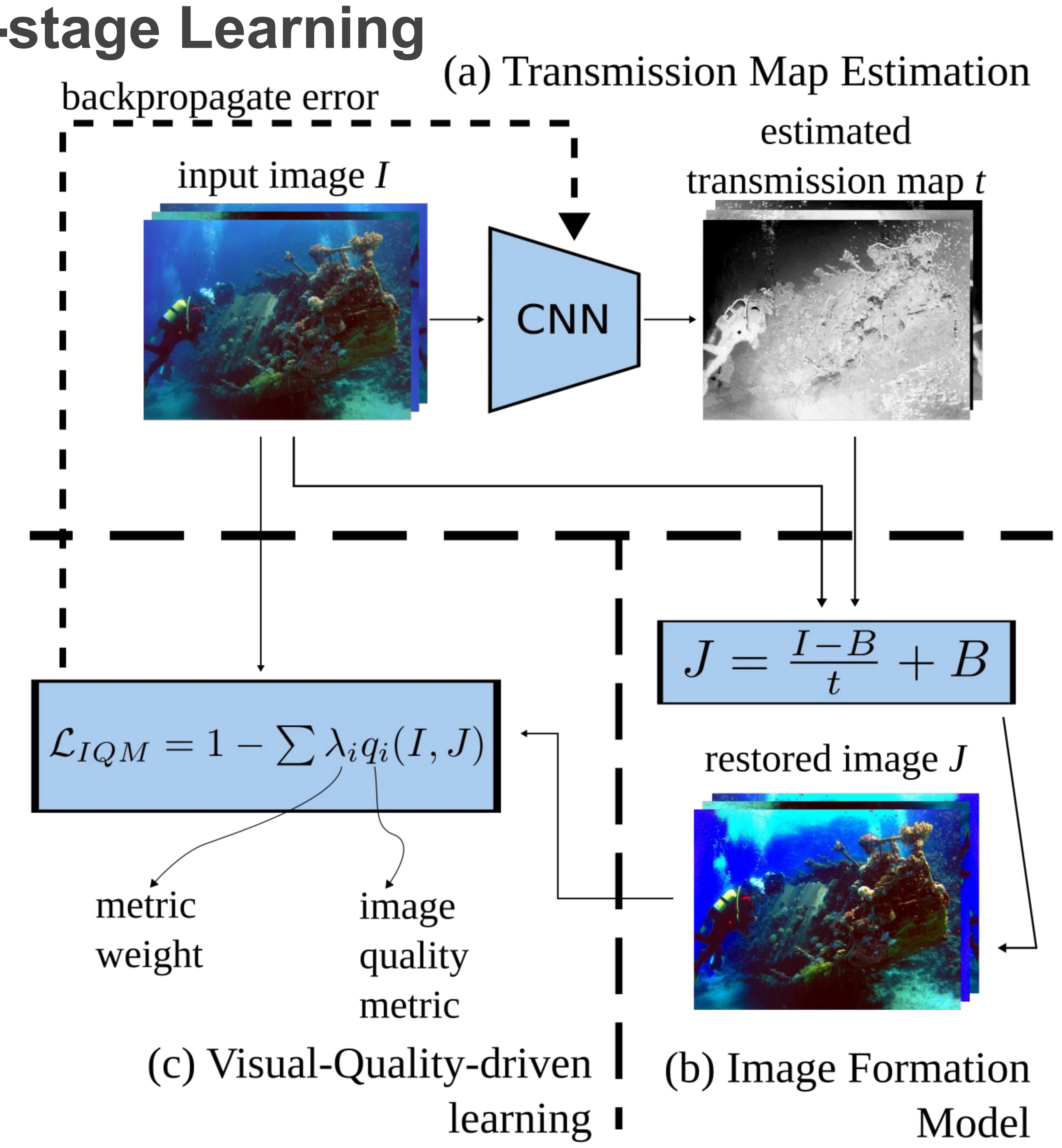
where λ_X is the weight for a feature gain q_X. $\mathcal{X}$ yields a multi-objective function that measures the enhancement of four features in the restored image in comparison to the input image.

Contrast Level	$q_C(I, J) = \frac{1}{n}\sum_{x=1}^{n}(C(J, x)^2 - C(I, x)^2)$
Accutance	$q_a(I, J) = \frac{1}{n}\sum_{x=1}^{n} G(J, x) - \frac{1}{n}\sum_{x=1}^{n} G(I, x)$
Border Integrity	$q_{BI} = \frac{\sum_{x=1}^{n}(E(J,x) \times E_d(I,x))}{\sum_{x=1}^{n} E_d(I,x)}$
Gray World Prior	$q_G(J) = (I_{max} - I_{min}) - \frac{2}{n}\sum_{x=1}^{n}(I(x) - 0.5(I_{min} + I_{max}))$

- The subsequent IQM loss function is minimized after computing all previous metrics:

$$\mathcal{L}_{IQM} = 1 - IQM(I, J).$$

Two-stage Learning



Metrics Evaluation

- Bold fonts indicate best results:

Table 1. Edges conservation (larger is better).

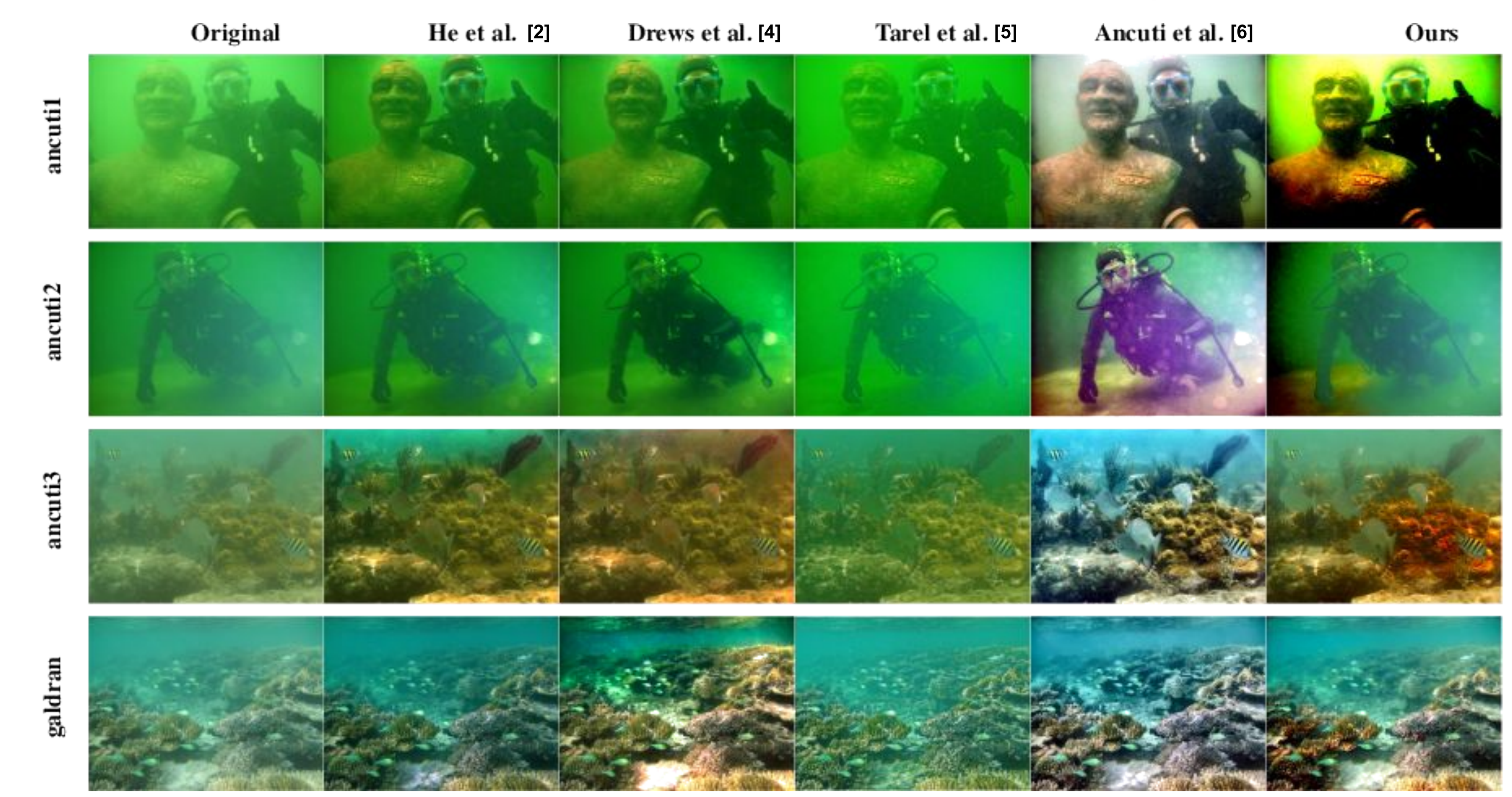
Scene	He	Drews	Ancuti	Ours
ancuti1	0.0000	0.0000	0.0003	**0.0855**
ancuti2	0.0000	0.0000	0.0006	**0.0192**
ancuti3	0.0000	0.0000	0.0008	**0.0009**
galdran	0.0004	0.0011	0.0062	**0.0280**

Table 2. Visual quality using UCIQE metric (larger is better).

Scene	Original	He	Tarel	Drews	Ancuti	Ours
ancuti1	0.8366	1.8894	0.5132	**2.7105**	1.8259	0.5359
ancuti2	0.4490	**1.2412**	0.4546	0.9285	1.1200	0.5497
ancuti3	0.7487	0.9458	0.5766	1.0913	1.0264	**4.0781**
galdran	0.9045	4.7779	0.5776	1.4077	4.0371	**6.9439**

Visual Results

- Higher blurriness is present in results from other techniques, while ours tends to preserve the valid scene edges.



References

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