Deep Unfolding Network With Physics-based Priors for Underwater Image Enhancement

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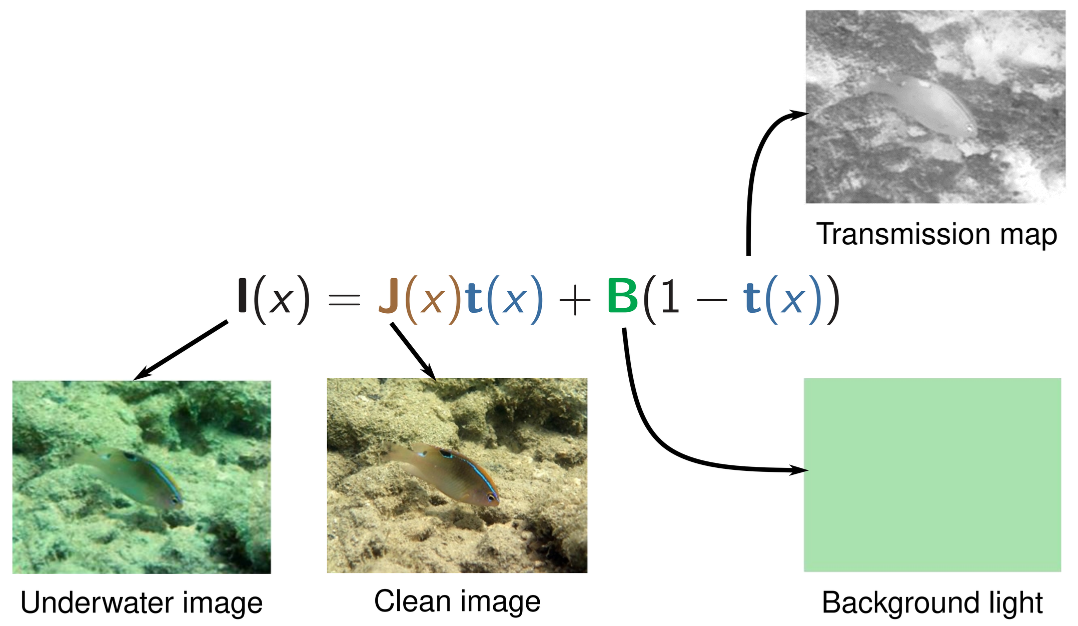
Abstract

We propose an underwater image enhancement algorithm that leverages both model- and learning-based approaches by unfolding an iterative algorithm. We first formulate the underwater image enhancement task as a joint optimization problem, based on the image formation model with physical model and underwater-related priors. Then, we solve the optimization problem iteratively. Finally, we unfold the iterative algorithm so that, at each iteration, the optimization variables and regularizers for image priors are updated by closed-form solutions and learned deep networks, respectively. Experimental results demonstrate that the proposed algorithm outperforms state-of-the-art underwater image enhancement algorithms.

Introduction

- Underwater images often suffer from quality degradation due to light absorption and scattering, reducing visibility and perceptual quality.



- Modeling inaccuracies may degrade the performance of model-based approaches.
- Learning-based algorithms behave as black boxes and rely on diverse training data, limiting their generalizability.
- In this work, we propose an unrolling approach for underwater image enhancement that unfolds an optimization problem into a learnable network.

Proposed Algorithm

- We formulate underwater image enhancement as a joint optimization problem with physical constraints and underwater-related priors as

$$\min_{\mathbf{J},\mathbf{t},\mathbf{B}} \frac{1}{2}\|\mathbf{J}\mathbf{t} + \mathbf{B}(\mathbf{1}-\mathbf{t}) - \mathbf{I}\|_2^2 + \underbrace{\frac{\gamma}{2}\|\mathbf{t} - \tilde{\mathbf{t}}_p\|_2^2}_{\text{Constraint on the transmission map}} + \underbrace{\mathcal{F}(\mathbf{J})}_{\text{Color prior}} + \underbrace{\varphi(\mathbf{B}) + \phi(\mathbf{J}) + \psi(\mathbf{t})}_{\text{Regularization terms}}$$

As handcrafted regularizers for $\mathbf{t}$ and $\mathbf{J}$ may not accurately capture real image features, we add three general regularization functions, φ, ϕ, and ψ, for $\mathbf{B}$, $\mathbf{J}$, and $\mathbf{t}$, respectively, learned from data.

- Variable separation

$$\min_{\mathbf{J},\mathbf{t},\mathbf{B},\mathbf{P},\mathbf{Q},\mathbf{R}} \frac{1}{2}\|\mathbf{J}\mathbf{t} + \mathbf{B}(1-\mathbf{t}) - \mathbf{I}\|_2^2 + \frac{\gamma}{2}\|\mathbf{t} - \tilde{\mathbf{t}}_p\|_2^2 + \varphi(\mathbf{P}) + \phi(\mathbf{Q}) + \psi(\mathbf{R}), \quad (1)$$

subject to $\mathbf{P} = \mathbf{B}$, $\mathbf{Q} = \mathbf{J}$, $\mathbf{R} = \mathbf{t}$.

Proposed Algorithm

- Solutions
  - Estimating the color-corrected image $\tilde{\mathbf{J}}$ by minimizing $\mathcal{F}(\mathbf{J})$

$$\tilde{\mathbf{J}}_m = \mathbf{J}_m + (\bar{\mathbf{J}}_l - \bar{\mathbf{J}}_m) \times \mathbf{J}_1 \quad (8)$$
$$\tilde{\mathbf{J}}_s = \mathbf{J}_s + (\bar{\mathbf{J}}_l - \bar{\mathbf{J}}_s) \times \mathbf{J}_l \quad (9)$$

  - Updating variables via closed-form solutions by an iterative technique

$$\mathbf{B}_k = \arg\min_{\mathbf{B}} \mathcal{L}(\mathbf{B}, \mathbf{t}_{k-1}, \mathbf{J}_{k-1}, \mathbf{P}_{k-1}, \mathbf{Q}_{k-1}, \mathbf{R}_{k-1}) \quad (15)$$
$$\mathbf{t}_k = \arg\min_{\mathbf{t}} \mathcal{L}(\mathbf{B}_k, \mathbf{t}_t\mathbf{J}_{k-1}, \mathbf{P}_{k-1}, \mathbf{Q}_{k-1}, \mathbf{R}_{k-1}) \quad (16)$$
$$\mathbf{J}_k = \arg\min_{\mathbf{J}} \mathcal{L}(\mathbf{B}_k, \mathbf{t}_k, \mathbf{J}, \mathbf{P}_{k-1}, \mathbf{Q}_{k-1}, \mathbf{R}_{k-1}) \quad (17)$$

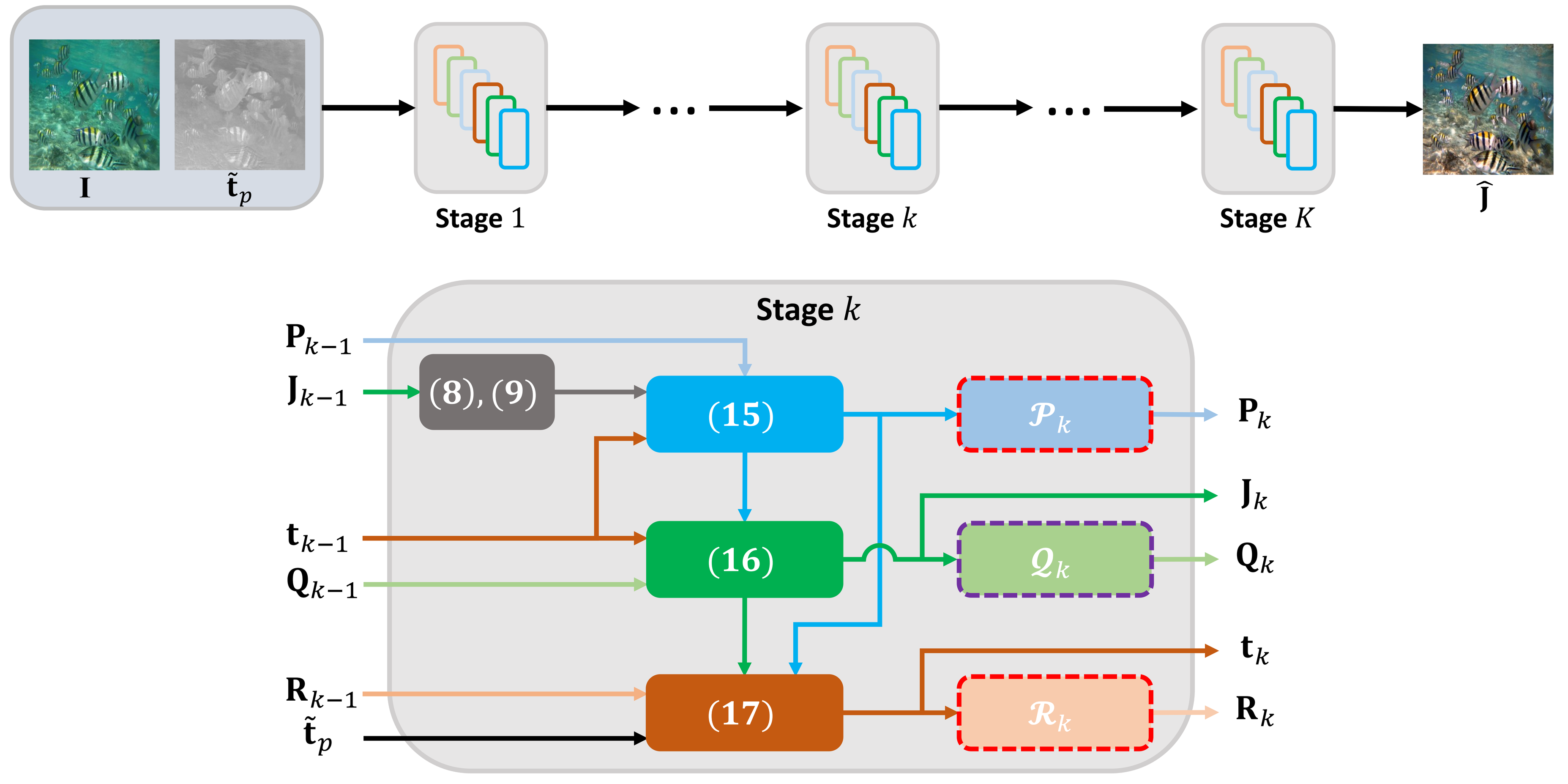
where $\mathcal{L}$ is the the augmented Lagrangian function derived from (1).

  - Learning prior information from the data via CNNs

$$\mathbf{P}_k = \arg\min_{\mathbf{P}} \mathcal{L}(\mathbf{B}_k, \mathbf{t}_k, \mathbf{J}, \mathbf{P}, \mathbf{Q}_{k-1}, \mathbf{R}_{k-1}) = \mathcal{P}_k(\mathbf{B}_k, \Gamma_{k-1}, \alpha_{k-1})$$
$$\mathbf{Q}_k = \arg\min_{\mathbf{P}} \mathcal{L}(\mathbf{B}_k, \mathbf{t}_k, \mathbf{J}, \mathbf{P}_k, \mathbf{Q}, \mathbf{R}_{k-1}) = \mathcal{Q}_k(\mathbf{J}_k, \mathbf{\Lambda}_{k-1}, \beta_{k-1})$$
$$\mathbf{R}_k = \arg\min_{\mathbf{P}} \mathcal{L}(\mathbf{B}_k, \mathbf{t}_k, \mathbf{J}, \mathbf{P}_k, \mathbf{Q}_k, \mathbf{R}) = \mathcal{R}_k(\mathbf{t}_k, \mathbb{1}_{k-1}, \eta_{k-1})$$

We employ a residual dense network (RDN) for $\mathcal{P}_k$ and $\mathcal{R}_k$ and an informative proximal mapping module (IPMM) for $\mathcal{Q}_k$.

Network Architecture



- l_1-norm of the difference between a ground-truth underwater image $\mathbf{J}_{\text{gt}}$ and an enhanced image $\hat{\mathbf{J}}$

$$L = \|\hat{\mathbf{J}} - \mathbf{J}_{\text{gt}}\|_1. \quad (2)$$

Experimental Results

Table: Quantitative comparison of underwater image enhancement performance using five objective quality metrics.

	IBLA [1]	HLRP [2]	MLLE [3]	FUnIE-GAN [4]	Water-Net [5]	Ucolor [6]	TACL [7]	Proposed
PSNR	15.22	12.55	17.78	16.97	15.76	21.08	23.25	**24.32**
SSIM	0.6632	0.2940	0.7513	0.7412	0.6755	0.8767	0.8590	**0.9313**
UCIQE	0.6002	0.6225	0.6216	0.5600	0.5285	0.5710	0.6100	**0.6244**
UIQM	**5.9023**	5.7807	4.3716	4.8814	4.5759	4.4183	4.2694	4.3973
NIQE	5.0339	4.7266	5.3187	4.7282	4.9934	4.7318	4.4941	**4.4847**

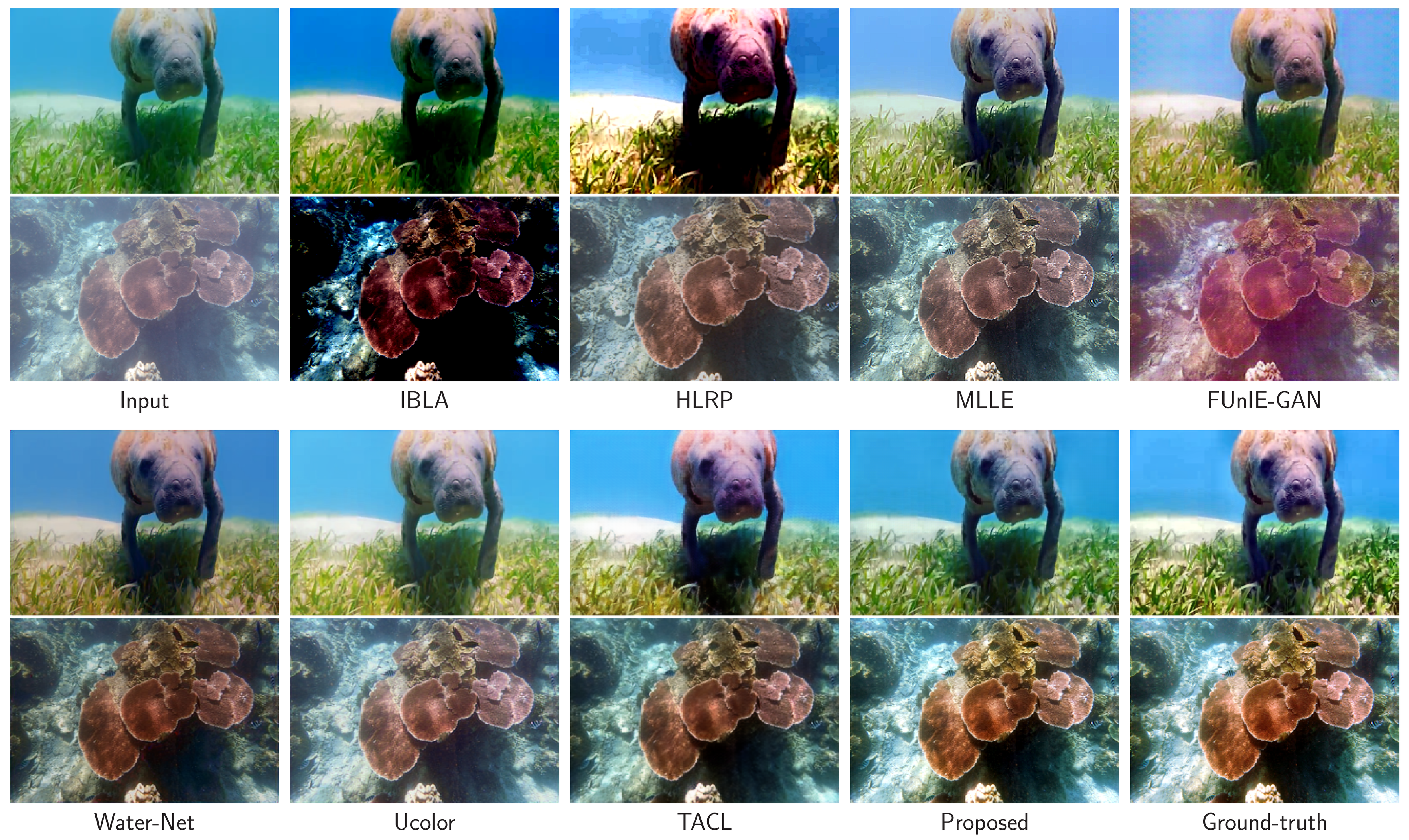


Figure: Comparison of the underwater image enhancement results on the UIEB dataset.

- Conventional algorithms yield poor results with low contrast and color distortions.
- Proposed algorithm provides the closest match to ground-truth and the most faithful enhancements.

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