A Nonconvex Approach for Restoring Underwater Images with Structural Priors

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Abstract

Due to the importance and practical applications of underwater images, we presented a method for restoring underwater images that incorporates structural information through regularization. Our method optimizes transmission maps using a nonconvex energy function with data and smoothness terms and includes static and dynamic structural priors in the smoothness term. Evaluation on a benchmark dataset shows that our approach performs well compared to state-of-the-art methods.

Ⅰ. Introduction

Underwater images are difficult to restore due to factors such as light absorption and scattering. This makes it difficult to detect underwater targets and navigate in the ocean. Restoring underwater images is important for various applications such as underwater robots and marine geological surveys. Underwater image restoration can be achieved through various methods including physics-based, non-physics-based, hardware-based, and deep learning-based models. Among these, physics-based methods such as guided filtering, statistical models, and matting algorithms attempt to improve the initial TM of an image by using man-made priors to compute desired parameters in the image formation model and inverting the model to generate a clearer image. Some examples of priors used in these methods include the DCP [1], UDCP [2], HDP [3], BP [4], HLP [5], and RCP [6]. However, these methods may not always produce satisfactory results due to their reliance on man-made priors.

In this work, we presented a method for improving the quality of underwater images through regularization and optimization. Our method effectively improves the transmission map and produces high-quality restored images that outperform state-of-the-art methods. The optimization process includes data and smoothness terms, with the smoothness term incorporating static and dynamic structural priors. The optimization problem is solved using the majorize-minimize algorithm. The proposed method is tested on a benchmark dataset and its performance is compared with state-of-the-art methods. The results from the experiments show that the proposed regularization scheme effectively improves the transmission map, which leads to high-quality restored images.

Ⅱ. Method

The proposed method for underwater image restoration (Fig. 1) consists of three steps: 1) calculating the veiling light and initial estimate of light transmission, 2) refining the initial estimate through a nonconvex energy framework that includes static and dynamic weights, and 3) restoring the image using the underwater imaging model. We use the model proposed in [7] to describe the image formation process in underwater environments.

$$I_c(\boldsymbol{x}) = J_c(\boldsymbol{x}) n_c(\boldsymbol{x}) + (1 - n_c(\boldsymbol{x})) \cdot A_c \quad , \tag{1}$$

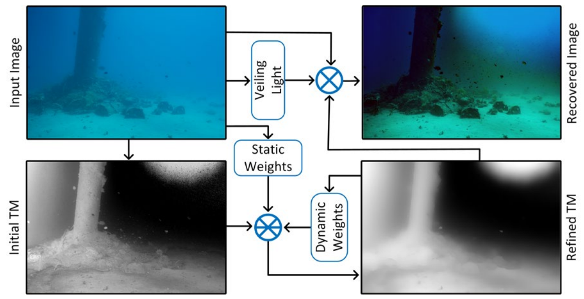

Figure 1: Proposed method for restoring underwater image with static and dynamic structural priors

This model separates the image into an object radiance component and a veiling light component. To estimate the veiling light and initial light transmission, we used the underwater haze lines prior [5]. This paper proposes optimizing the initial TM n by efficiently minimizing the following energy function as:

$$\mathcal{E}(\hat{n}) = \sum_{x\in\Omega} (\hat{n}(x) - n(x))^2 + \lambda \sum_{x\in\Omega} \sum_{x'\in\mathcal{N}_x} w_{x,x'}(s)\ \psi_\rho(\hat{n}(x) - \hat{n}(x')), \tag{2}$$

where the first term is the data fidelity term and the second one is the regularization term. In the proposed regularizer, $w_{x,x'}(s)$ is the spatially varying weighting function computed from guidance s as:

$$w_{x,x'}(s) = \exp(-\mu(x - x')^2)\exp(-\nu(s(x) - s(x'))^2)\,, \tag{3}$$

The proposed robust regularizer is the parameterized squared hyperbolic tangent function defined as:

$$\psi_\rho(\hat{n}(x) - \hat{n}(x')) = \tanh(\rho(\hat{n}(x) - \hat{n}(x'))^2), \tag{4}$$

We minimized the non-convex energy function Eq. 2 using the majorize-minimize algorithm. At each iteration, this algorithm creates a convex surrogate function and finds a local minimum. At the majorization step, $E^{(k)}$ for $\mathcal{E}$ is achieved by substituting the regularizer $\psi_\rho(j)$ with $\Psi_\rho^i(j)$ as:

$$E^{(k)}(\hat{n}) = \sum_{x\in\Omega} [(\hat{n}(x) - n(x))^2 + \lambda \sum_{x'\in\mathcal{N}_x} w_{x,x'}(s) \Psi_\rho^{(\hat{n}^{(k)}(x) - \hat{n}^{(k)}(x'))} (\hat{n}(x) - \hat{n}(x'))], \tag{5}$$

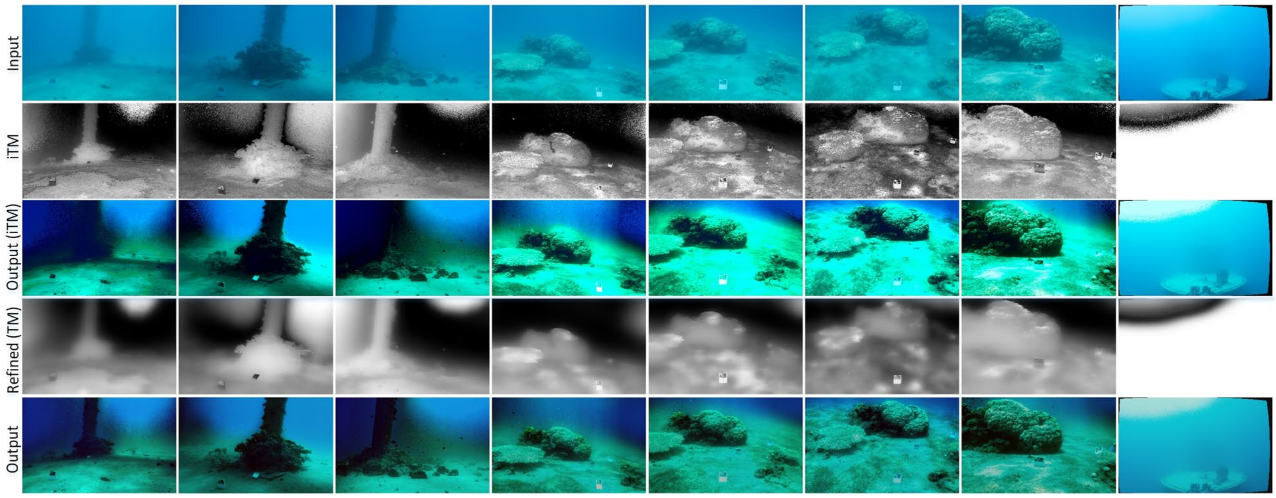

Figure 2: Effectiveness of our proposed method in improving the initial transmission maps and the resulting quality of the restored images. The input images, selected randomly from each dataset, are listed in Table 1.

where $\Psi_\rho^i(j)$ is a surrogate function for $\psi_\rho(j)$.

The goal of underwater image restoration is to recover the scene radiance $J(x)$ from $I(x)$ based on Eq. 2 as:

$$J(x) = \frac{I(x) - V}{\hat{n}(x)} + V \quad (8)$$

Ⅲ. Results

Our method is compared to other methods using datasets and evaluation metrics from [5]. The effectiveness of the TMs is measured using the Pearson correlation coefficient ρ with values closer to 1 indicating better estimation. The average angular error ψ for restored color is calculated using $\cos^{-1}$, with lower angle values indicating better color restoration. The proposed method for improving underwater images involves the use of regularization parameters $\lambda = 500$, $\mu = 0.02$, $\nu = 200$, and $\rho = 3$. We applied this method to a set of 8 stereo pairs from 4 different datasets and found that our method resulted in improved transmission maps and the quality of restored images. The quantitative analysis for the results shown in Figure 2 can be seen in Table 1.

Images	Initial ρ	Refined ρ	Initial ψ	Refined ψ
RGT_4479	0.7289	0.8777	35.62	29.83
RGT_4487	0.79	0.8432	34.51	30.90
RGT_5455	0.6477	0.7705	30.25	27.47
RGT_5466	0.7595	0.823	34.58	30.96
RGT_3014	0.7443	0.8225	34.18	30.40
RGT_3272	0.8027	0.8616	35.66	31.16
RGT_4318	0.3117	0.3609	39.85	28.98
RGT_4382	0.0649	0.0764	35.45	31.87

Table 1: Quantitative measure for the results shown in Fig. 2

The proposed method for improving underwater images is compared to several state-of-the-art transmission refinement methods, including Guided Filter [8], Mutual Structure Filtering [9], Soft Matting [10], SD Filtering [11]. We found that all of these methods are able to improve initial transmission maps, but the results of the proposed method (RR) are superior in terms of improving the TMs, avoiding abrupt color variations and preserving object texture details.

Ⅳ. Conclusion

In this paper, we proposed a method for enhancing the quality of underwater images using regularization techniques. Our method is able to improve upon initial transmission maps, leading to higher-quality restored images.

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