Physics-inspired Learning for Structure-Aware Texture-Sensitive Underwater Image Enhancement

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Abstract

Recently, improving the visual quality of underwater images using deep learning-based methods has drawn considerable attention. Unfortunately, diverse environmental factors (e.g., blue/green color distortion) severely limit their performance in real-world environments. Therefore, strengthening the superiority of the underwater image enhancement method is critical. In this paper, we devote ourselves to develop a new architecture with strong superiority and adaptability. Inspired by the underwater imaging principle, we establish a novel physics-inspired learning model that is easy to realize. A Structure-Aware Texture-Sensitive Network (SATS-Net) is further developed to portray the model. The structure-aware module is responsible for structural information, and the texture-sensitive module is responsible for textural information. Thus, SATS-Net successfully incorporates robust characterization absorbed from the physical principle to achieve strong robustness and adaptability. We conduct extensive experiments to demonstrate that SATS-Net outperforms existing advanced techniques in various real-world underwater environments.

Keywords: Underwater image enhancement, physics-inspired, structure-aware, texture-sensitive

1. Introduction

With the extensive development of underwater geological exploration, underwater biological detection, target recognition, and other underwater applications, high-quality underwater images are critical for these applications. However, owing to the scattering and absorption effects of the underwater environment, visual images often have problems such as low contrast, blurring, and color distortion. Therefore, underwater image enhancement remains challenging.

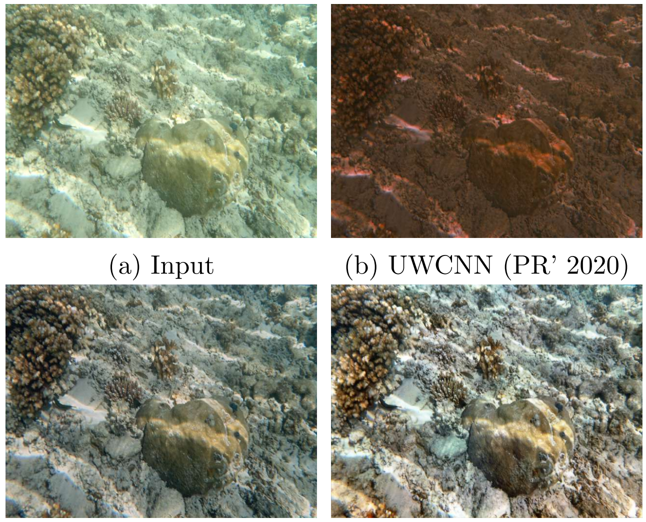
1.1. Related Work

To improve the visibility of the underwater degraded image, numerous enhancement technologies have been proposed. To investigate underwater image enhancement methods, we classified these methods into three broad categories: classical enhancement, physical model-based, and deep learning-based methods.

Classical Enhancement Methods. Classical enhancement methods aim to modify the pixel values of an image to improve the visual quality. These methods use color correction algorithms such as white balance Liu et al. (1995), gray-scale edge assumption Van De Weijer et al. (2007), and contrast enhancement algorithms such as histogram equalization, which demonstrates better results when processing normal images. Ancuti et al. (2012) adopted a fusion strategy that combines the color-corrected and contrast-enhanced versions of an underwater image. Fu et al. (2014) presented a Retinex-based enhancing approach to enhance a single underwater image. Zhang et al. (2017) presented a method inspired by the Retinex framework. They used a combination of bilateral and trilateral filters to simulate underwater turbidity conditions. A histogram distribution prior was proposed to increase the contrast and brightness of underwater images Li et al. (2016). Fu et al. (2017) proposed a two-step approach for underwater image enhancement useing a color correction algorithm, followed by a contrast enhancement algorithm. Gao et al. (2019) adopted feedback from color-sensitive horizontal cells to cones and red channel compensation to correct non-uniform color bias.

Physical Model-based Methods. Physical model-based methods consider underwater image enhancement as an inverse problem of image degradation. They usually address the inverse problem by establishing a physical underwater image model to estimate unknown model parameters from the effect image prior. Carlevaris-Bianco et al. (2010) proposed a method to predict the transmission of an underwater scene. Galdran et al. (2015) attempted to employ the optical properties of underwater imaging to restore the colors associated with short wavelengths. Drews et al. (2016) presented an underwater dark channel prior based on the dark channel prior for underwater image enhancement. Liu and Chau (2016) maximized the image contrast by developing a cost function and minimizing it to find the optimal transmission map. Li et al. (2017) adopted the random forest regression and estimated the transmission map of the underwater image. Peng et al. (2018) proposed a generalised dark channel prior, which can accurately estimate the background light and underwater scene depth for underwater images.

Deep Learning-based Methods. In addition to the above methods, various studies have extended their work to adopt deep learning for underwater image enhancement. Deep learning-based methods construct deep neural networks and train them between degraded underwater images and high-quality references. Fabbri et al. (2018) presented an unsupervised method to combine a new attention module and a new learnable normalized function in an end-to-end manner. Uplavikar et al. (2019) synthesized images of different types of water from indoor environment images to train generative adversarial networks. Islam et al. (2020) proposed a novel dataset EUVP, which divides the network into two



(a) Input (b) UWCNN (PR' 2020)

(c) WaterNet (TIP' 2019) (d) Ours

Figure 1: Visual comparison on a real underwater image enhancement result between two state-of-the-art approaches and our method. Our method achieves the best visual expression with color correct and the most texture information.

parts for training. Li et al. (2019) constructed an underwater image enhancement benchmark with the corresponding reference images. Moreover, they proposed an underwater image enhancement fusion network to combine three traditional methods. Li et al. (2020) employed a convolutional neural network based on underwater scene prior for underwater image enhancement. Xue et al. (2021) reformulated the task as luminance reconstruction and chrominance correction subtasks by separating the luminance and chrominance of underwater images.

However, although these methods have some effects on improving image quality, they also have inevitable disadvantages, and the image processing results obtained using these methods are not always ideal in diverse underwater environments. To overcome these limitations, our network is inspired by the physical model, that is starting from the underwater image formation model to estimate structure and texture features by decomposing the object image. Our SATS-Net significantly outperforms the previous methods in real-world underwater dataset.

1.2. Our Contributions

To promote superiority and adaptability for underwater image enhancement methods, we built a novel physics-inspired learning model reconstructed from an underwater imaging model that is relatively easy to implement. In particular, we develop a Structure-Aware Texture-Sensitive Network (SATS-Net) that leverages Structure-Aware Enhancement (SAE) module to learn the structural information for recovering the degraded image primarily, and the Texture-Sensitive Enhancement (TSE) module is devised to extract the textural information for further enhancement. As shown in Figure. 1, our method can enhance the underwater degraded image with color and texture recovery. Several exper-

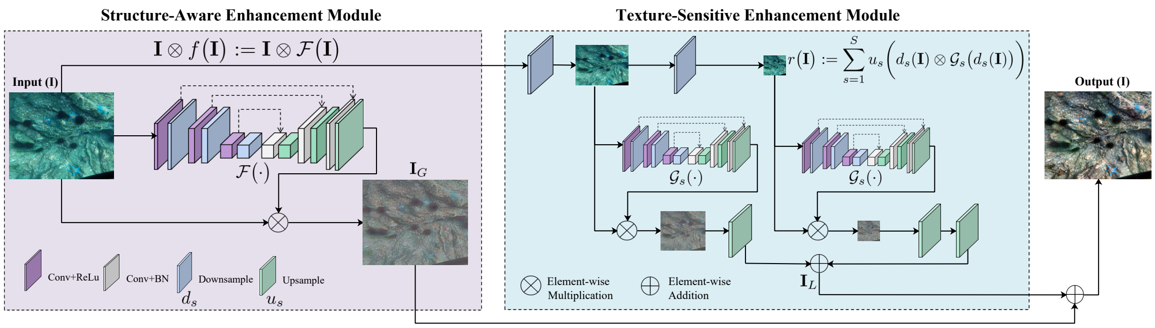


Figure 2: Overview of the proposed STAS-Net. In which, the SAE module improves visual quality from the entire structural expression. The TSE module focuses on enhancing local textural information.

iments conducte to demonstrate the effectiveness of the proposed network. Overall, our contributions can be summarized as follows:

- To strengthen the superiority and adaptability of the underwater enhancement method, we develop a fresh physics-inspired learning model for underwater images by reformulating the solving scheme derived from the underwater imaging model.
- We propose a novel SATS-Net network that has two crucial components. The SAE module is responsible for the structural information to achieve primary enhancement, and the TSE module takes charge of textural information to be further enhanced.
- Extensive quantitative and qualitative comparisons are conducted to demonstrate our outstanding performance against state-of-the-art approaches. We also present internal analysis to demonstrate the effectiveness of the modules we employed.

2. The Proposed Method

In this section, we first introduce the physics-inspired learning model, and then we design the SATS-Net to implement the model. Finally, we describe training loss.

2.1. Physics-Inspired Learning Model

Our method is inspired by the underwater Image Formation Model (IFM) developed by McGlamery (1980), which can help us to design a robust and effective model for underwater images. According to the IFM model, the underwater image $\mathbf{I}(x)$ captured by the camera can be represented as follows:

$$\mathbf{I}(x) = \mathbf{J}(x) \cdot \mathbf{t}(x) + A(1 - \mathbf{t}(x)), \tag{1}$$

where $\mathbf{J}(x)$ is the scene radiance, $\mathbf{t}(x)$ refers to the transmission, and $\mathbf{A}$ denotes the background light. According to the model expressed in Eq. (1), we can derive the following equation:

$$\mathbf{J}(x) = \mathbf{I}(x) \cdot \frac{1}{\mathbf{t}(x)} + A\big(1 - \frac{1}{\mathbf{t}(x)}\big). \tag{2}$$

Many unknown parameters must be estimated for using this model, which results in a large amount of computation. Therefore, we develope a more compact model, defined as follows:

$$\mathbf{J} = \mathbf{I} \otimes f\big(\mathbf{I}\big) + r\big(\mathbf{I}\big), \tag{3}$$

where the function $\mathbf{f}(\cdot)$ is defined to calculate $\frac{1}{t}$. We summarize the rest of $\mathbf{r}(\mathbf{I})$, which is the function calculated from the background light $\mathbf{A}$ and transmission $\mathbf{t}$. The operator $\otimes$ denotes the element-wise multiplication.

Note that the model structure has two crucial components: $\mathbf{I} \otimes f\big(\mathbf{I}\big)$ represents structural information to recover the distorted color and reduced contrast, whereas $r\big(\mathbf{I}\big)$ represents the textural information to enhance the details of underwater degraded images. Finally, we obtain the output of this model by adding two parts.

2.2. SATS-Net

Figure. 2 shows the architecture of the proposed SATS-Net for underwater image enhancement. The SATS-Net comprises two modules: a SAE module and a TSE module.

2.2.1. Structure-Aware Enhancement Module

The SAE module aims to enhance the underwater image by learning the structural information (illumination). We first estimate the feature map of the input image and then perform a multiplication that can be expressed as $\mathbf{I} \otimes f\big(\mathbf{I}\big)$. To implement this, we define a structure-aware function $\mathcal{F}\big(\cdot\big)$ to estimate the illumination map.

As shown in the left half of Figure. 2, given input image $\mathbf{I} \in R^{H \times W \times C}$, we can compute the output $\mathbf{I}_G$ of the SAE module using the following equation:

$$\mathbf{I}_G = \mathbf{I} \otimes \mathcal{F}\big(\mathbf{I}\big). \tag{4}$$

With this module, the underwater image is globally enhanced, as shown in the second column of Figure 3. To further enhance and achieve a better visual effect, we employ a local-sensitive network to achieve ultimate enhancement. This is introduced in the following subsection.

2.2.2. Texture-Sensitive Enhancement Module

Considering the texture information critical in underwater images, we develope the TSE module to learn textural information $r\big(\mathbf{I}\big)$, resulting in a more effective enhancement.

As shown in the right half of Figure. 2, we first use the down-sampling layers denoted as d_s to obtain the small-scale image. Each down-sampling operation yields an image with half the size of the input image. We define $\mathcal{G}_s\big(\cdot\big)$ as a texture-sensitive function for learning texture information. Additionally, considering the final visual effect and the running speed of the network, we select two networks in this part. We define the TSE module using the following equation:

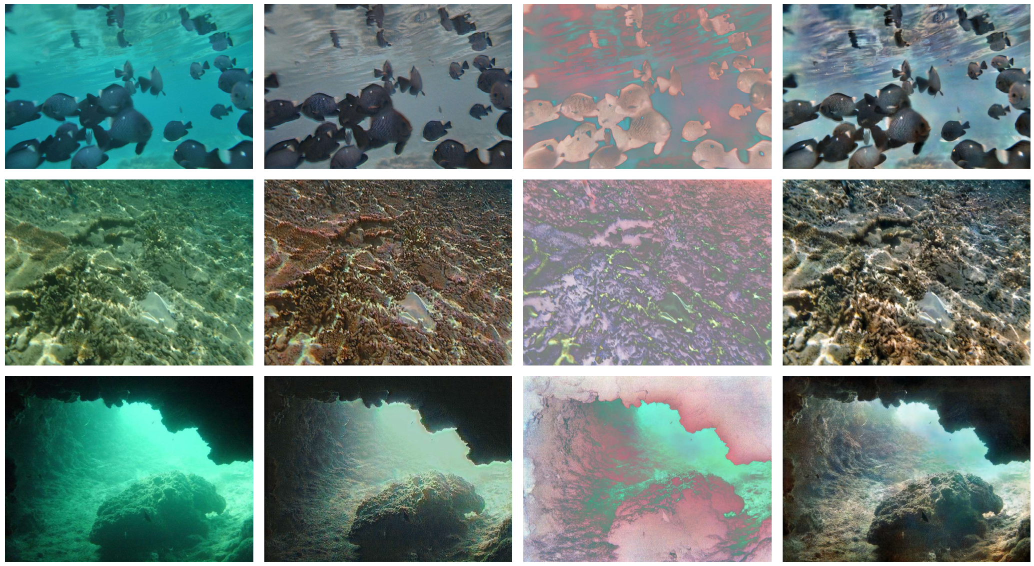


Figure 3: Visualization of intermediate results. The middle two columns represent the outputs of SAE and TSE modules.

$$\mathbf{I}_L = \sum_{s=1}^{S} u_s\Big(d_s(\mathbf{I}) \otimes \mathcal{G}_s\big(d_s(\mathbf{I})\big)\Big), \tag{5}$$

where d_s denotes the down-sampling operation, u_s represents the upsample operation, which restores the size of the downsampled low-scale image, and s denotes the number of networks in the TSE module.

As shown in the third column of Figure. 3, the TSE module learns texture information to further enhance the underwater image. Finally, we obtain the result from the addition of the SAE and TSE modules, and the final outputs are shown in the fourth column of Figure. 3.

2.3. Training Loss

We use MS-SSIM loss Seshadrinathan and Bovik (2009) and the MSE loss to measure the reconstruction accuracy in the training process. The MS-SSIM loss is an SSIM loss function based on multi-layer (image from large to small), which takes into account the resolution of the image. The MSE is the mean square error, which first calculates the square of each pixel difference between the distorted image and the original image, and then takes the mean. Formally, the reconstruction loss function can be written as follows:

$$\mathcal{L} = \mu\mathcal{L}^{MS-SSIM} + (1-\mu)\mathcal{L}^{MSE}, \tag{6}$$

where μ is set to 0.8. $\mathcal{L}^{MS-SSIM}$ and $\mathcal{L}^{MSE}$ represent the losses of MS-SSIM and MSE, respectively.

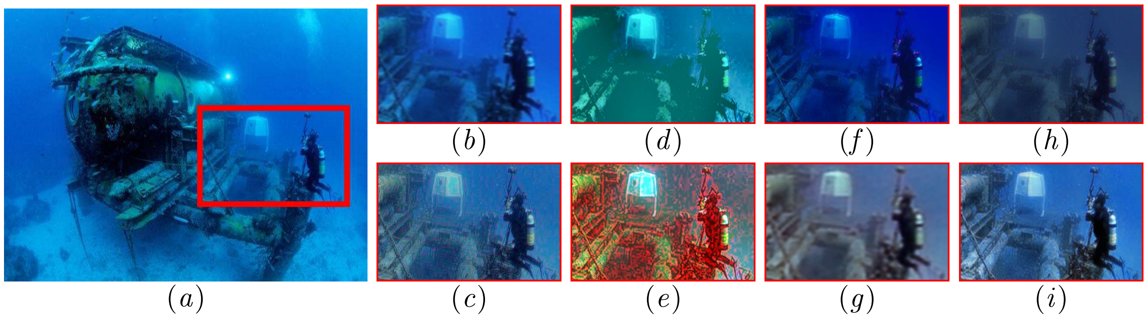


Figure 4: Visual results of state-of-the-art methods and ours on UIEB-S dataset. Red boxes indicate the obvious differences. (a) is the input underwater image. (b)-(i) are the enhanced results of different methods. (b) FGAN, (c) WaterNet, (d) TSA, (e) OCM, (f) UDCP, (g) UGAN, (h) UWCNN, and (i)Ours.

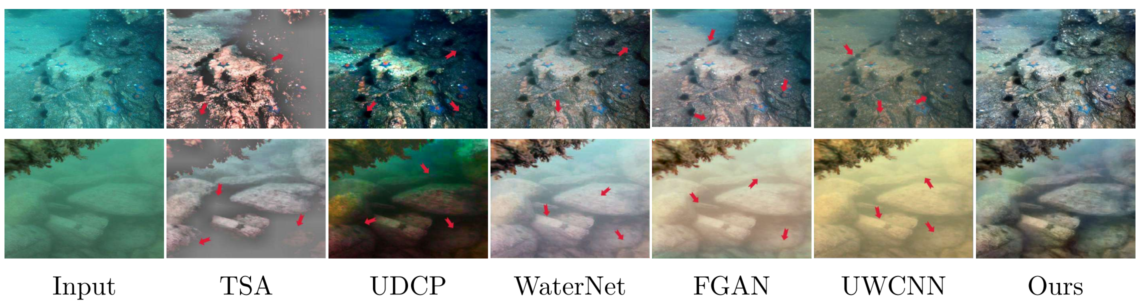


Figure 5: Visual comparisons of enhancement results from UCCS datasets. *Zoom in for best view.*

3. Experiments and Analyses

3.1. Implementation Details

In our experiment, the proposed model was implemented using Pytorch and executed on two GeForce RTX 2080Ti GPUs with a batch size of six. We used a random set of 712 paired images from Underwater Image Enhancement Benchmark (UIEB) Li et al. (2019) as our training set. It is widely used to resize training data to a fixed size in deep learning. Thus, we resized the training data to a size of 640 $\times$ 480. Furthermore, we used the Adam optimizer Kingma and Ba (2014) with an initial learning rate of 1×10^{-4} and decreased the learning rate by 0.02 every 100 epochs. The whole network was trained end-to-end.

Datasets. All the experiments were tested on two benchmark datasets, the UIEB dataset Li et al. (2019) and Underwater Color Cast Set (UCCS) Liu et al. (2020) dataset. The UIEB dataset includes 950 real-world underwater images. We sampled 178 paired images (UIEB-S) and 60 challenging images (UIEB-C) without reference images as our testing set. The UCCS dataset contains 300 images of blue, green, and blue-green tones. We employed the 300 images from UCCS as our testing set.

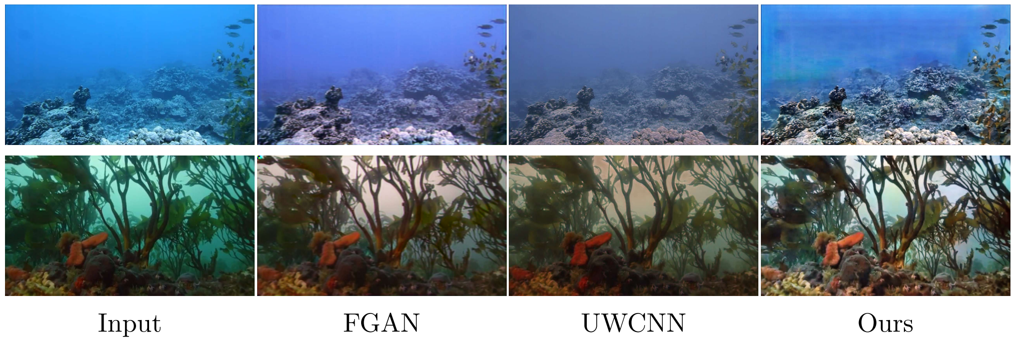


Figure 6: Comparison results on UIEB-C dataset.

3.2. Comparison with State-of-the-art Methods

To demonstrate the validity of the proposed method, we conducted the subjective and objective comparisons of several state-of-the-art underwater image enhancement methods, including EUIVF Ancuti et al. (2012), UDCP Drews et al. (2016), TSA Fu et al. (2017). Moreover, several representative deep learning-based methods, i.e. AIO Uplavikar et al. (2019) , UGAN Fabbri et al. (2018), UWCNN Li et al. (2020), FGAN Islam et al. (2020), OCM Li et al. (2016) and WaterNet Li et al. (2019) are presented to further prove the adaptability of the proposed method in real-world complex underwater scenes.

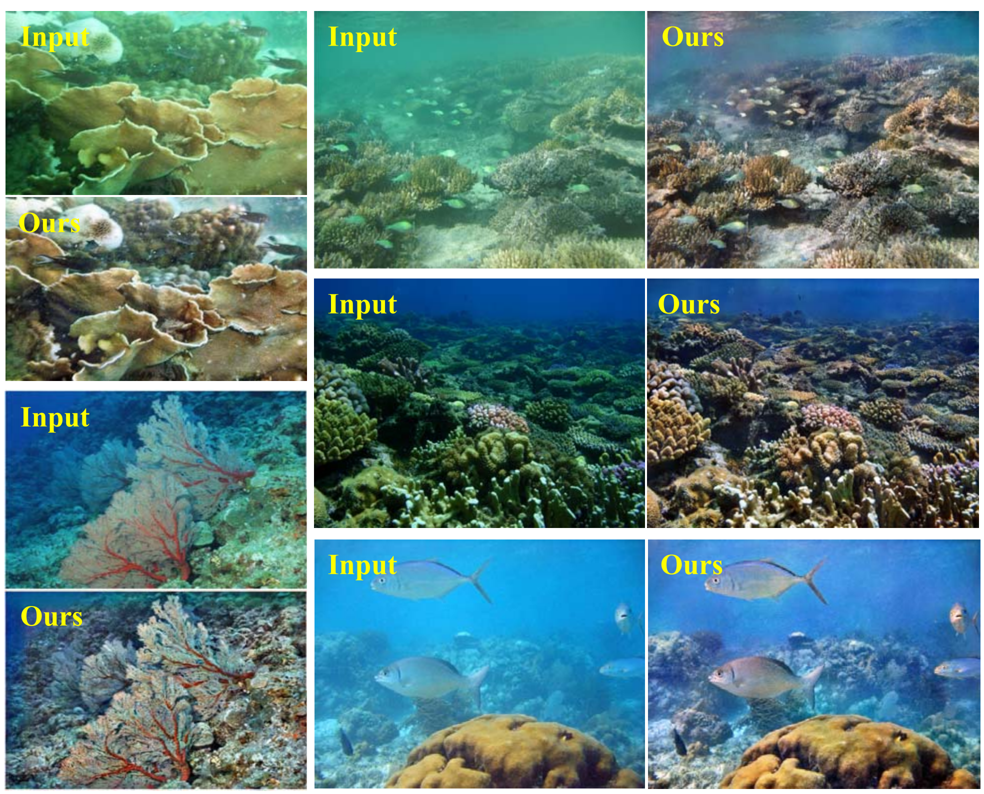


Figure 7: More results from real-world underwater scenarios.

Table 1: Quantitative performance comparisons on three commonly-used testing datasets. Best results are denoted in **red** and the second best results are denoted in **blue**.

Dataset	Metric	EUIVF	UDCP	OCM	TSA	UGAN
UCCS	UIQM↑	3.073	2.098	2.912	2.512	3.043
	NIQE ↓	4.542	5.131	4.537	4.842	6.680
UIEB-S	UIQM↑	**2.757**	1.772	2.512	1.996	1.870
	NIQE ↓	4.048	4.304	**3.873**	4.166	7.057
UIEB-C	UIQM↑	2.076	1.102	1.830	1.326	**2.830**
	NIQE ↓	**5.136**	6.499	5.236	5.294	6.858
Dataset	Metric	AIO	WaterNet	UWCNN	FGAN	Ours
UCCS	UIQM↑	3.137	**3.150**	2.536	2.982	**3.518**
	NIQE ↓	5.637	4.543	**4.411**	5.696	**4.292**
UIEB-S	UIQM↑	2.746	2.307	2.428	2.512	**3.150**
	NIQE ↓	9.202	4.485	4.488	6.364	**3.864**
UIEB-C	UIQM↑	2.304	2.245	1.824	2.514	**2.598**
	NIQE ↓	8.976	5.824	6.673	7.010	**5.057**

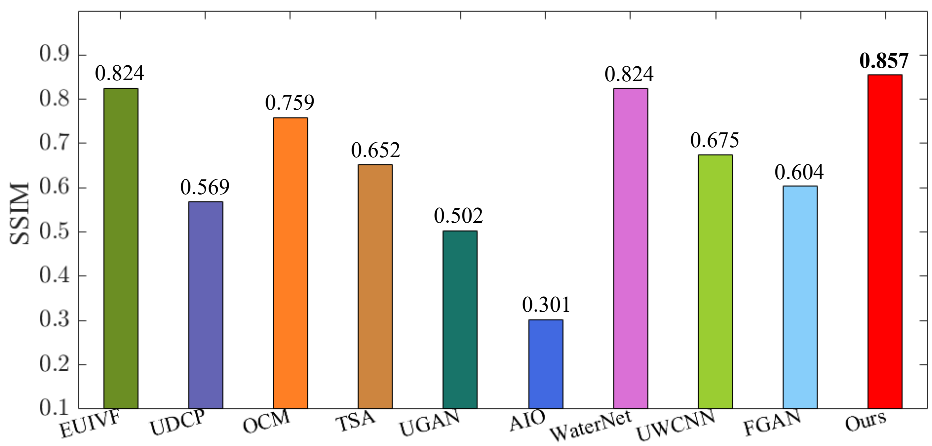
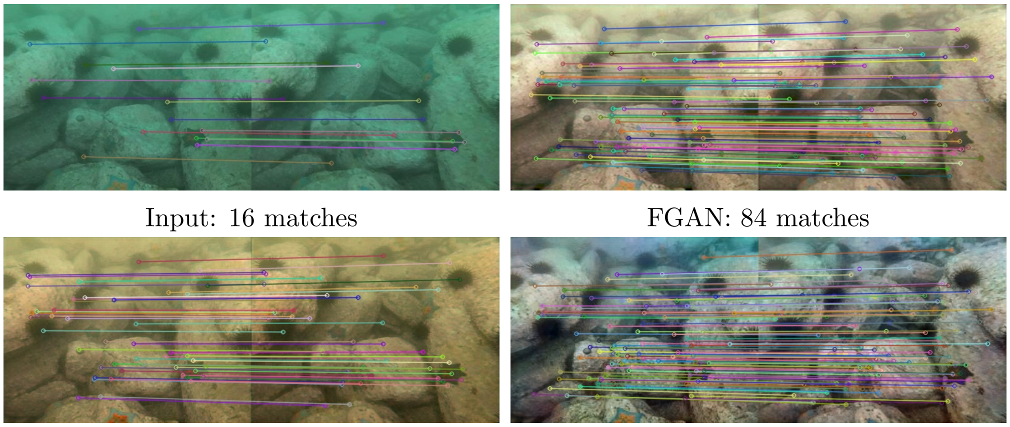


Figure 8: Quantitative comparisons (SSIM) on UIEB-S dataset.

Subjective Evaluation. Figure. 4 presents a visual comparison of nine different underwater image enhancement methods on the UIEB-S testing set. As shown from the results, the competing methods cannot recover the appropriate color of underwater scenes (e.g., FGAN Islam et al. (2020), UDCP Drews et al. (2016)) and introduce unexpected colors (e.g. TSA Fu et al. (2017), OCM Li et al. (2016)) or have little veil-effect residuals (e.g., UGAN Fabbri et al. (2018), UWCNN Li et al. (2020), WaterNet Li et al. (2019)). In contrary, Our results have more realistic color and textural information.

Figure. 5 shows the comparison results, which show that our method produces the best visual results for the UCCS testing set. The visual experience of our method not only corrects the color cast but also enhances the details of image visibility. Meanwhile, most of the competing methods introduce unexpected colors. WaterNet and FGAN can



Input: 16 matches | FGAN: 84 matches

UWCNN: 48 matches | Ours: **97** matches

Figure 9: Matching result comparisons on UIEB-C dataset.

partially enhance underwater images, however, it is difficult to process severe degradation phenomena. Figure. 6 shows the results of the UIEB-C dataset. While state-of-the-art methods fail to remove veil and correct color, our method results on the UIEB-C dataset are more convincing.

Figure. 7 shows our results for various real-world underwater environments. Our method performs well in all types of underwater environments, demonstrating the powerful generalization ability of our approach.

Objective Evaluation. For the objective evaluation, we adopted the metric SSIM to evaluate the structural property under the paired data, the Underwater Image Quality Measure (UIQM) Panetta et al. (2015) and the Natural Image Quality Evaluator (NIQE) Mittal et al. (2012) to evaluate under the unpaired data. To observe the quantitative performance intuitively, we used a histogram to show the SSIM metric results, which are shown in Figure. 8. The UIQM and NIQE values are shown in Table 1. By comparison, our method clearly outperforms the others.

Application of Local Keypoints Matching. We further test the effectiveness of our method by adopting local keypoints matching on the UCCS dataset between the input and output of our network, which aims to find correspondences between two similar scenarios. Figure. 9 shows the results of the matching. Note that the input matches 16 keypoints, the underwater enhancement methods FGAN and UWCNN match 84 and 48 keypoints while our method matches 97 points. The enhanced image pairs significantly increased the number of keypoints. Our method recovers local features better than state-of-the-art methods for underwater images.

3.3. Analysis and Discussion

In this part, we present important analytical experiments to further reflect the necessity of our network.

First, we analyzed the effectiveness of the proposed TSE module. We tested the effect of the TSE module on the UIEB-S dataset. In Table 2, the first row denoted as $\mathcal{M}_1$ shows that removing the TSE module causes the performance drop. Subsequently, the internal

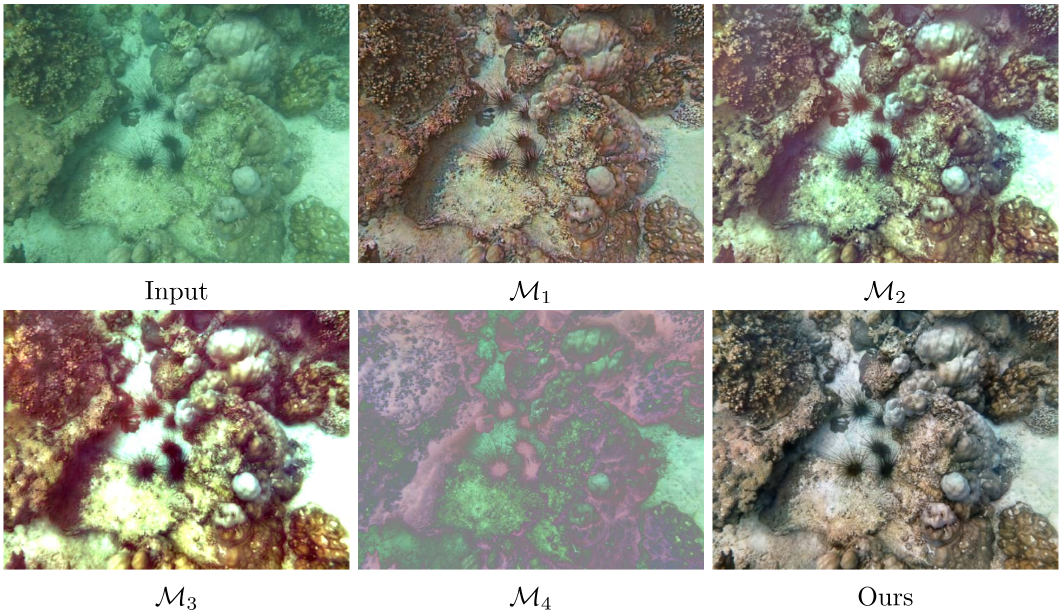


Figure 10: Visual results of ablation analysis.

network structure of the TSE module is analyzed, which can be divided into $\mathcal{M}_2$ and $\mathcal{M}_3$ according to the number of subnetworks. The method $\mathcal{M}_4$ proves the indispensability of the SAE module. As shown in Table 2 the proposed network performs better than the aforementioned analysis methods. Figure. 10 shows the visual results of each analysis structure, demonstrating the advantage of jointly learning structure-aware and texture-sensitive underwater image enhancement network.

Table 2: Ablation analysis for the proposed network.

	w/ SAE	w/o TSE	w/ TSE			Metrics	
			S=1	S=2	S=3	SSIM	NIQE
$\mathcal{M}_1$	$\surd$	$\surd$	$\times$	$\times$	$\times$	0.810	3.948
$\mathcal{M}_2$	$\surd$	$\times$	$\surd$	$\times$	$\times$	0.787	4.057
$\mathcal{M}_3$	$\surd$	$\times$	$\times$	$\times$	$\surd$	0.705	4.167
$\mathcal{M}_4$	$\times$	$\times$	$\times$	$\surd$	$\times$	0.321	4.231
Ours	$\surd$	$\times$	$\times$	$\surd$	$\times$	**0.857**	**3.864**

4. CONCLUSION

In this paper, we have established a physics-inspired learning model. The proposed model learns both structural and textual information to enhance the underwater image through two aspects. We also present its detailed network architecture SATS-Net, associated loss functions, and end-to-end training pipeline. Extensive experiments have demonstrated the superiority of our solution and the effectiveness of SATS-Net.

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