

# SyreaNet: A Physically Guided Underwater Image Enhancement Framework **Integrating Synthetic and Real Images**

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# **1. Introduction**

Underwater Image Enhancement (UIE) is important for high-level vision-related underwater tasks. However, current learningbased methods have difficulty in consistently deal with various underwater conditions, which could be caused by:

- The prevalent usage of the simplified atmospheric image formation model.
- The network trained solely with synthetic images might have difficulty in generalizing well to real underwater 1mages.

In this work, we propose *SyreaNet*, a UIE framework combining both synthetic and real underwater images guided by the revised underwater image formation model and novel domain adaptation (DA) strategies.

# 2.1 Physically Guided Synthesis Module

The expression for synthesizing an underwater image based on the revised model is:

 $I_c(x) = J_s(x)W_c e^{-\hat{\beta}_c^D(z)z} + \hat{B}_c(x)$ where  $I_c(x)$  is the synthesized underwater image,  $J_s(x)$  is the in-air image,  $W_c$  is the white point of the ambient light,  $\hat{\beta}_{c}^{D}$  is the wideband attenuation coefficient,  $\hat{B}_c(x)$  is the estimated backscattering. The figure below shows some examples of synthesized images:





real underwater images



underwater images

# 2. Proposed Method

As shown below, synthetic underwater images are first generated by our proposed physically guided synthesis module (PGSM). Then various synthetic and real underwater images are fed into the physically guided disentangled network. The intra- and inter-DAs are done by exchanging the knowledge across attribute domains and training with our well designed loss functions.







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	Intra-Synthetic-Domain Adaptation
	Intra-Real-Domain Adaptation
	Inter-Domain Adaptation
PGSM	Physically Guided Synthesis Module
PGDNet	Physically Guided Disentangle Network
RIFM	Revised Image Formation Module
UIG	Underwater Image Generator
ST	Style Transferor
UID	Underwater Image Discriminator
$\rightarrow$	Synthetic Data Flow
>	Intra-Synthetic-Domain Data Flow
	Real Data Flow
>	Intra-Real-Domain Data Flow
$\rightarrow$	Underwater Discriminator Data Flow
···· <b>&gt;</b>	Inter-Domain Data Flow



Our proposed method also achieves state-of-the-art performance in metrics of UIQM/UCIQE and gets the lowest RGB error:

Meth

UIQM↑

### UCIQE↑

### RGB E



## 4. Conclusions

In this study, we have proposed a novel UIE framework SyreaNet that combines synthetic and real data under the guidance of the revised underwater image formation model and DA strategies. Extensive experiments indicate that our framework outperforms previous SOTA learningbased UIE approaches in restoring the original color and details of degraded underwater images.

### References

# **2.3 Intra- and Inter-Domain**

- For intra-synthetic-DA, the clear backgrounds are kept invariant while the disentangled components' knowledge is exchanged. Revised image formation module (RIFM) is used to formulate synthetic underwater images directly.
- For intra-real-DA, the clear underwater backgrounds and exchanged components are recombined with an underwater image generator (UIG).
- For inter-DA, the clear background knowledge is exchanged with a style transferor (ST), and the exchanged backgrounds and disentangled components are fed into UIG to generate synthetic underwater images.

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# **3. Experimental Results**

The qualitative results are shown below:



UWCNN

WaterNe

C R A

L O N D O N · 2 0 2 3

nods		AIO	GLNet	WaterNet	UColor	SyreaNet	
	UIEB	1.069	1.598	1.315	1.372	1.656	
	EUVP	1.021	1.359	1.213	1.247	1.363	
	UIEB	0.506	0.619	0.543	0.558	0.582	
	EUVP	0.497	0.614	0.523	0.541	0.578	
Error↓		26.574	10.488	12.167	11.332	5.158	

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