Contrastive Semi-supervised Learning for Underwater Image Restoration via Reliable Bank

Shirui Huang[1,+], Keyan Wang[1,+,*], Huan Liu[2], Jun Chen[2], Yunsong Li[1]

*Equal Contributions, +Corresponding Author,
1. Xidian University, 2. McMaster University

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Preview of Underwater Benchmarks

❖ Lack of real data: domain gap

(a)

(b)

(c)

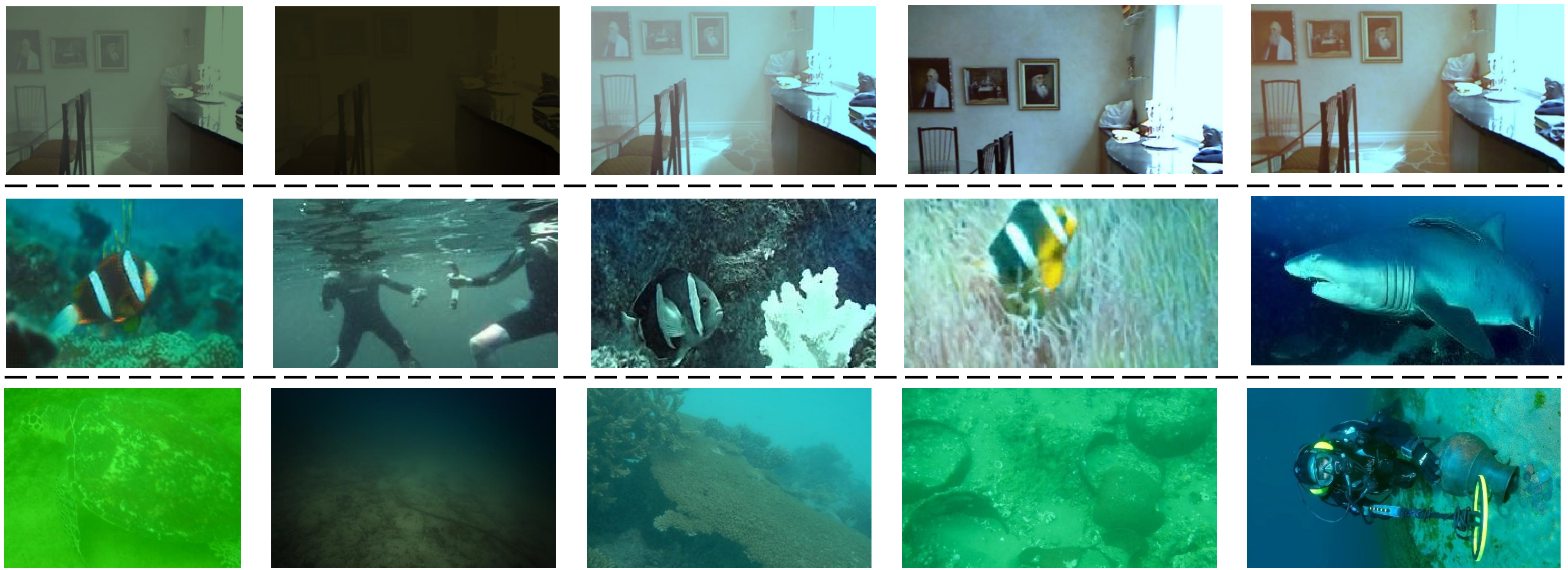


Figure 1. Examples from different benchmarks.

❖ Limited data size:

dataset	UIEB	ImageNet	COCO
Number	890	>14,000,000	200,000

Motivation – Semi-supervised Learning

- Flowchart of SSL

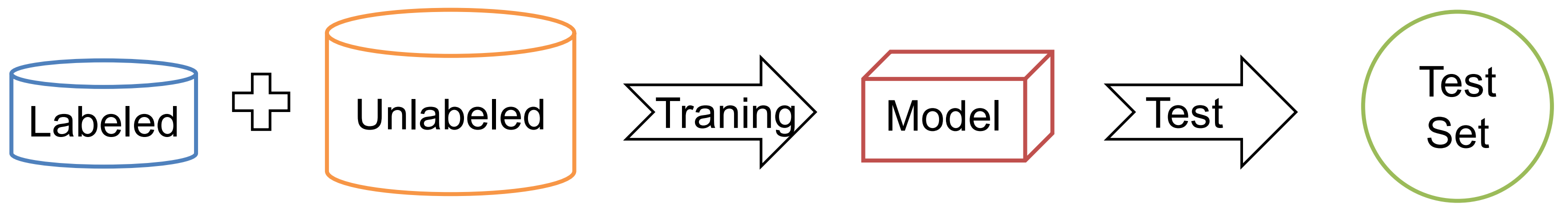


Figure 2. Semi-supervised learning

- Mean-teacher Framework

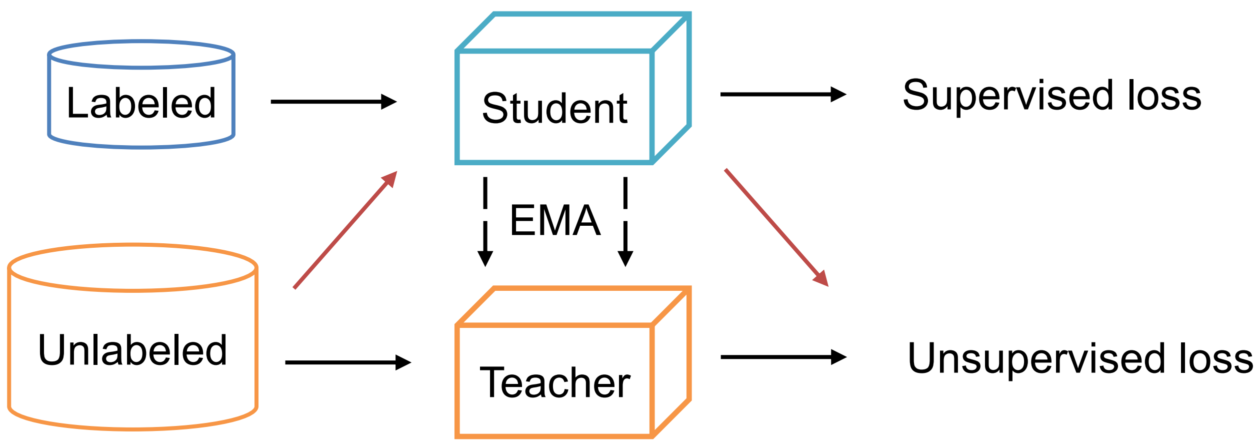


Figure 3. Framework of mean-teacher

1) The consistency loss used in training might become ineffective when the teacher's prediction is wrong
2) Using L1 distance may cause the network to overfit wrong labels, resulting in confirmation bias

Method – Semi-UIR

❖ Contributions:

1) SSL framework improves the **generalization** of the trained model on real-world data
2) **Reliable bank** stores best-ever teacher outputs and ensures the reliability of pseudo-labels
3) **Contrastive loss** works as a regularization form to alleviate confirmation bias

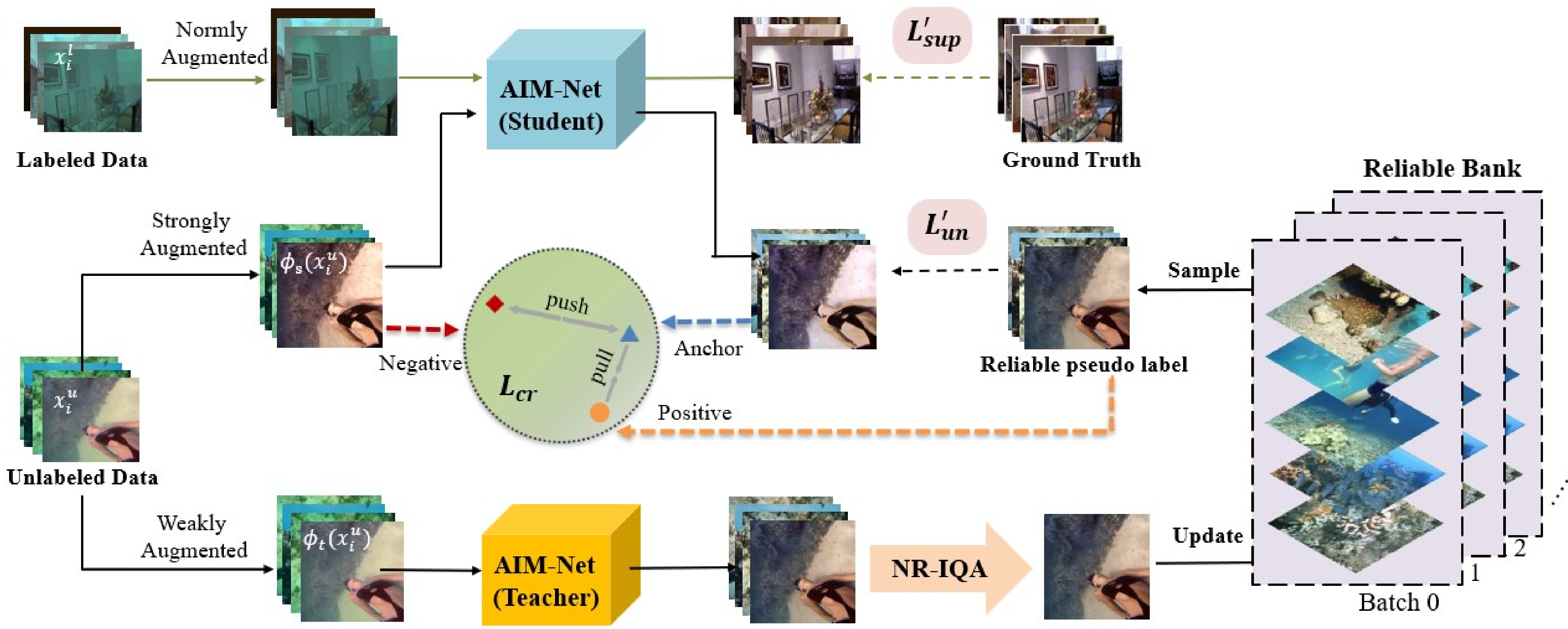


Figure 4. Illustration of our framework Semi-UIR

Method – Reliable Teacher-student Consistency

- Wrong pseudo labels can potentially **jeopardize** the training of the student network

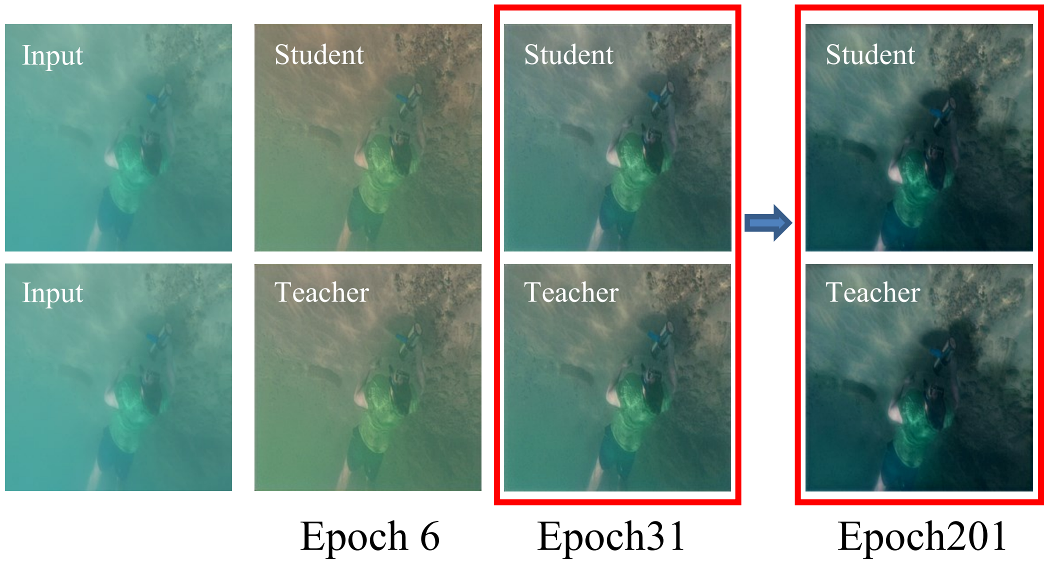


Figure 5. Examples of unreliable consistency

$$L_{un}^{'} = \sum_{i=0}^{M} \left| f_{\theta_s}(\phi_s(x_i^u) - y_i^b \right|$$

Algorithm 1 Update of Reliable Bank

Require: NR-IQA method $\Psi(\cdot)$;
Initialize $\mathcal{B}_U = \emptyset$;
Sample a batch of unlabeled images $\{x_i^u\}_{i=1}^b$ from D_U;
for each x_i^u **do**
  Get teacher's prediction: $\hat{y}_i^u = f_{\theta_t}(\phi_t(x_i^u))$;
  Get student prediction: $\tilde{y}_i^u = f_{\theta_s}(\phi_s(x_i^u))$;
  Compute NR-IQA scores of $\hat{y}_i^u$, $\tilde{y}_i^u$ and $y_i^b \in \mathcal{B}_U$:
  $z_t = \Psi(\hat{y}_i^u)$, $z_s = \Psi(\tilde{y}_i^u)$, $z_b = \Psi(y_i^b)$;
  if $z_t > z_s$ and $z_t > z_p$ **then**
    Replace the y_i^b in $\mathcal{B}_U$ by $\hat{y}_i^u$;
  end if
end for

Figure 6. Update of reliable bank

- To address the issue, we propose a **reliable bank** to store the **best-ever outputs** of the teacher network during the training process

Method – Reliable Metric Selection

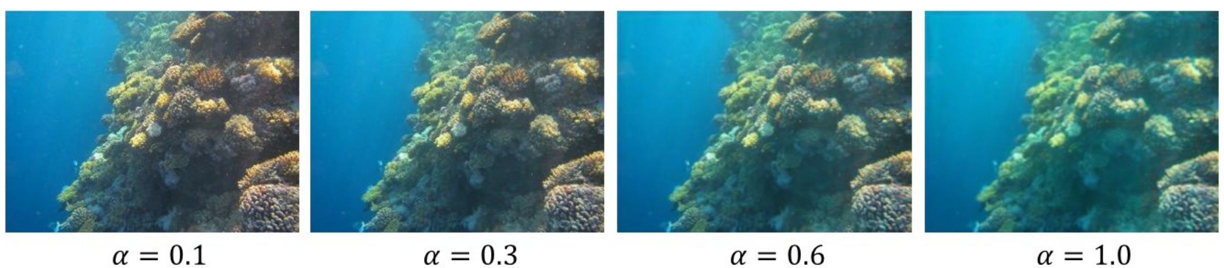
❖ Empirical analysis

Degraded image: $\boldsymbol{x}$ Clean image: $\boldsymbol{y}$

Fusion coefficient: $\boldsymbol{\alpha_i = 1 \times i, i = 1, \ldots, 10}$

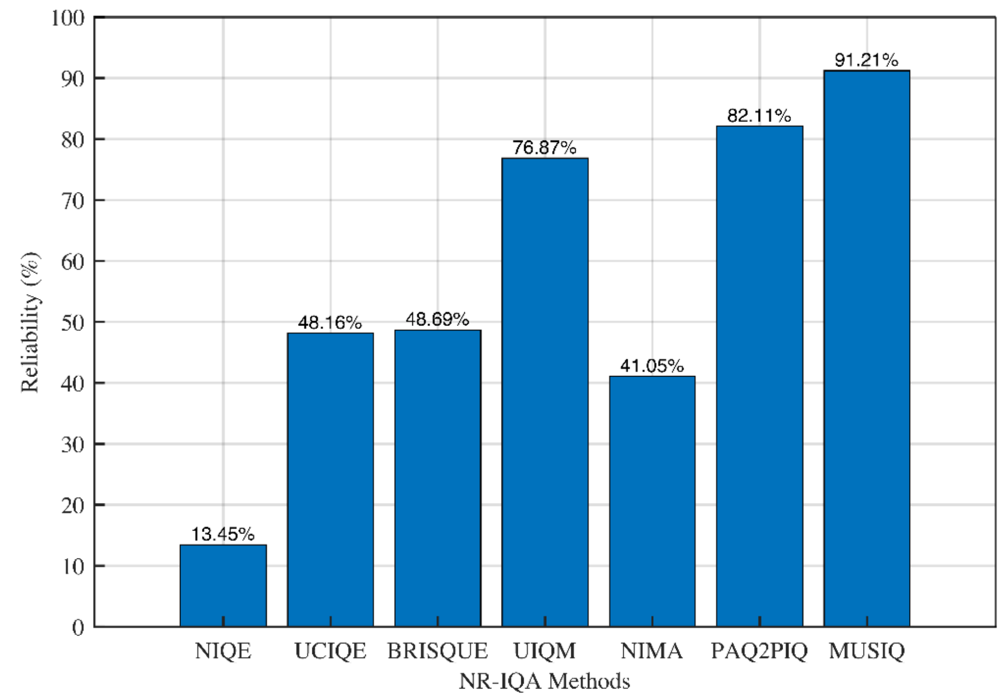
Linear combination: $\boldsymbol{z_i = \alpha_i \times x + (1 - \alpha_i) \times y}$

Figure 7. Exampes of image fusion based on different α



❖ Monotonicity law

Figure 8. The results of seven non-reference IQA indicators on EUVP benchmark, **MUSIQ wins!**



An NR-IQA metric is identified as **reliable** if its score on $\boldsymbol{z_i}$ decreases with the increase of α

Method – Contrastive Regularization

- To alleviate **confirmation bias**, we introduce contrastive loss in the training
- How to construct positive & negative pairs and feature space?

$\boldsymbol{y_i^b}$ $\rightarrow$ Positive sample, reliable label

$\boldsymbol{\phi_s(x_i^u)}$ $\rightarrow$ Negative sampe, strongly augmented

$\boldsymbol{y_i^u}$ $\rightarrow$ Anchor, student's outpur

VGG-19 $\rightarrow$ Feature space

$$L_{cr} = \sum_{j=1}^{K} \sum_{i=1}^{M} \omega_j \frac{\left|\varphi_j(y_i^u), \varphi_j(y_i^b)\right|}{\left|\varphi_j(y_i^u), \varphi_j(x_i^u)\right|}$$

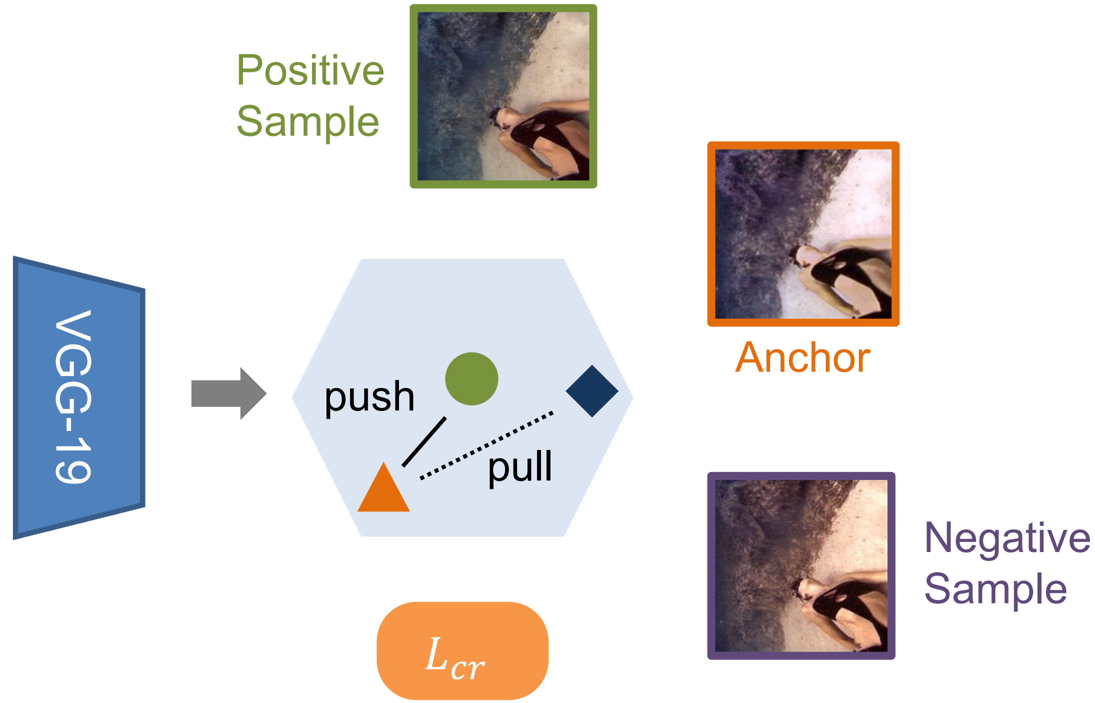


Figure 9. Contrastive loss

Method – Underwater Restoration Network

- Certain prior information: illumination prior, gradient prior

- Two branches: illumination-aware restoration branch and gradient branch

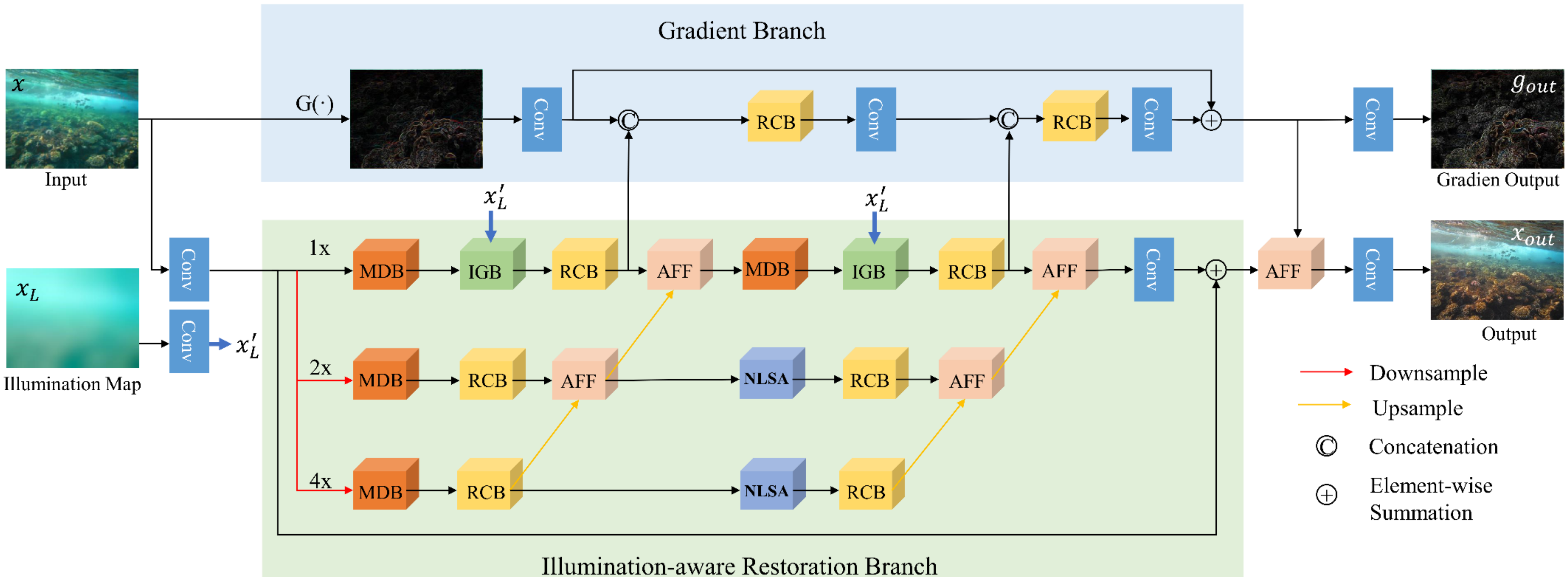


Figure 10. Structure of AIM-Net

Experiments – Quantitative Results

Table 1. Quantitative results on full-reference datasets

Method	testS		testR	
	PSNR↑	SSIM↑	PSNR↑	SSIM↑
Input	14.64	0.641	18.23	0.746
GDCP [33]	12.89	0.576	15.78	0.757
MMLE [53]	12.76	0.651	20.01	0.781
WaterNet [22]	15.44	0.706	21.58	0.858
Ucolor [20]	23.32	**0.853**	22.92	0.881
PRWNet [16]	17.27	0.723	20.98	0.848
FGAN [17]	18.54	0.743	19.41	0.824
CWR [11]	14.79	0.697	21.87	0.815
Semi-UIR	**23.40**	0.821	**24.59**	**0.901**

Table 2. Quantitative results on four non-reference datasets

Method	UIQM (higher, better)				UCIQE (higher, better)				MUSIQ (higher, better)			
	UIEB	EUVP	RUIE	Seathru	UIEB	EUVP	RUIE	Seathru	UIEB	EUVP	RUIE	Seathru
Input	3.066	4.729	3.948	5.925	0.509	0.517	0.490	0.537	41.70	42.73	33.53	60.25
GDCP [29]	3.401	4.738	4.509	5.343	0.564	**0.599**	0.565	0.590	40.07	42.49	34.63	60.54
MMLE [47]	4.283	4.723	**4.967**	5.555	0.578	0.596	0.571	0.620	40.33	47.55	36.80	66.16
WaterNet [19]	4.118	5.317	4.568	6.829	0.572	0.595	**0.572**	0.610	40.32	43.07	32.23	64.38
Ucolor [17]	3.894	5.286	4.426	6.752	0.542	0.566	0.534	0.594	40.08	41.81	33.66	64.44
PRWNet [13]	4.371	**5.330**	4.395	6.778	0.518	0.543	0.518	0.572	40.30	43.52	33.12	62.82
FGAN [14]	4.315	4.469	4.519	4.853	0.541	0.561	0.527	0.564	40.95	43.36	34.48	64.25
CWR [8]	4.133	5.152	4.469	6.067	**0.587**	0.596	0.565	0.624	38.46	41.46	31.25	64.21
Semi-UIR	**4.598**	5.291	4.671	**6.846**	**0.587**	0.593	0.557	**0.632**	**43.77**	**51.66**	**37.87**	**66.61**

Experiments – Qualitative Results

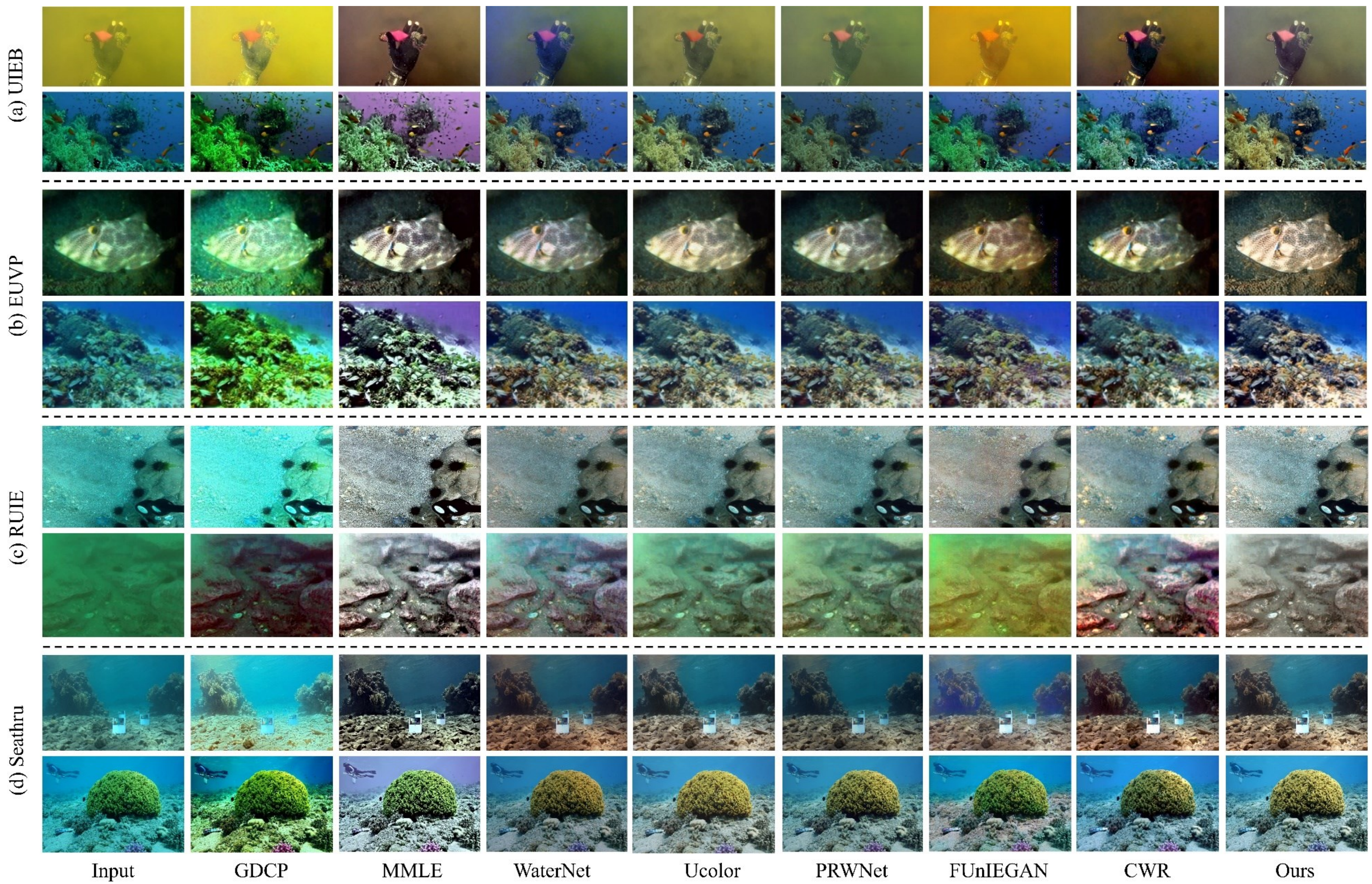


Figure 11. Qualitative Results

Experiments – Influence of innovation points

❖ Breakdown of training

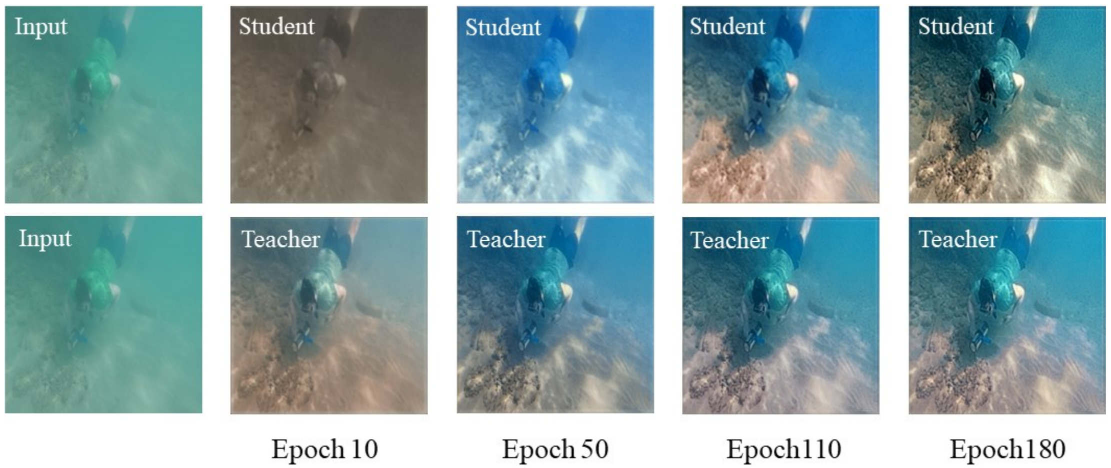


Figure 12. Examples of intermediate predictions

❖ Data Augmentation

Table3. Evaluation of using different data augmentation

Strategy	testR	UIEB	EUVP	RUIE	Seathru
Baseline	0.880	40.12	46.06	31.14	64.71
Color Jitter	0.889	40.31	49.16	33.66	64.87
Gaussian Blur	0.896	41.23	49.27	36.88	64.88
Gray Scale	0.895	40.61	47.57	32.51	65.19
All	**0.901**	**43.77**	**51.66**	**37.87**	**66.61**

❖ Non-reference Metric

Table4. Evaluation of adopting different NR-IQA metrics

	NIQE	NIMA	UCIQE	BRISQUE	UIQM	PAQ2PIQ	MUSIQ
Reliability	13.45%	41.05%	48.16%	48.69%	76.87%	82.11%	91.21%
testS	22.83/0.811	23.01/0.815	22.90/0.813	23.15/0.820	23.24/0.820	23.08/0.818	23.40/0.821
testR	22.98/0.887	23.88/0.888	23.64/0.890	24.00/0.900	23.80/0.897	24.28/0.893	24.59/0.901

Thank you!

XIDIAN UNIVERSITY 1931

McMaster University