中国科学院软件研究所学术年会 2025 第十届
暨重点实验室科技活动周
学术论文

基于因果孪生网络的持续测试时单图像散焦模糊去除

Continual Test-Time Adaptation for Single Image Defocus Deblurring via Causal Siamese Networks

(International Journal of Computer Vision (2025) 133:4134–4157)

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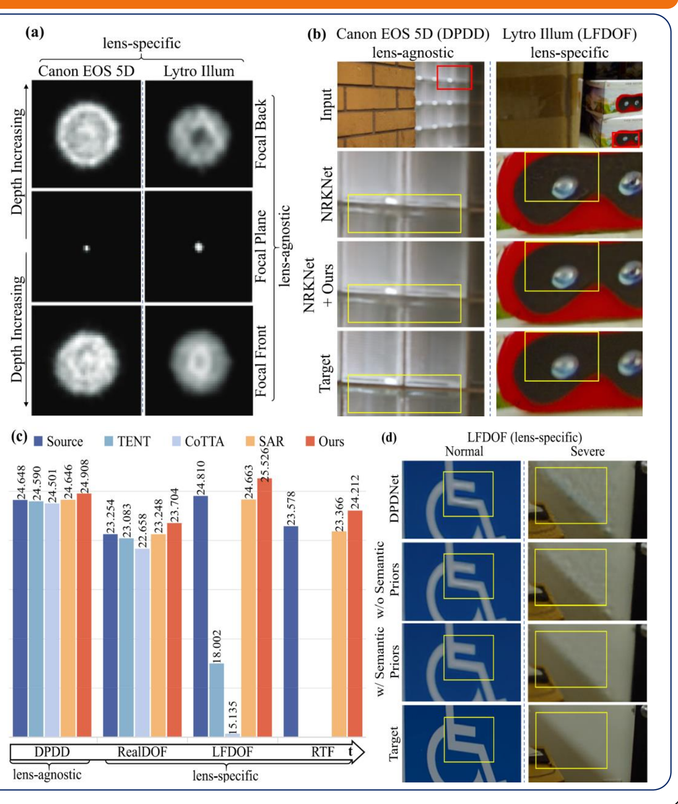
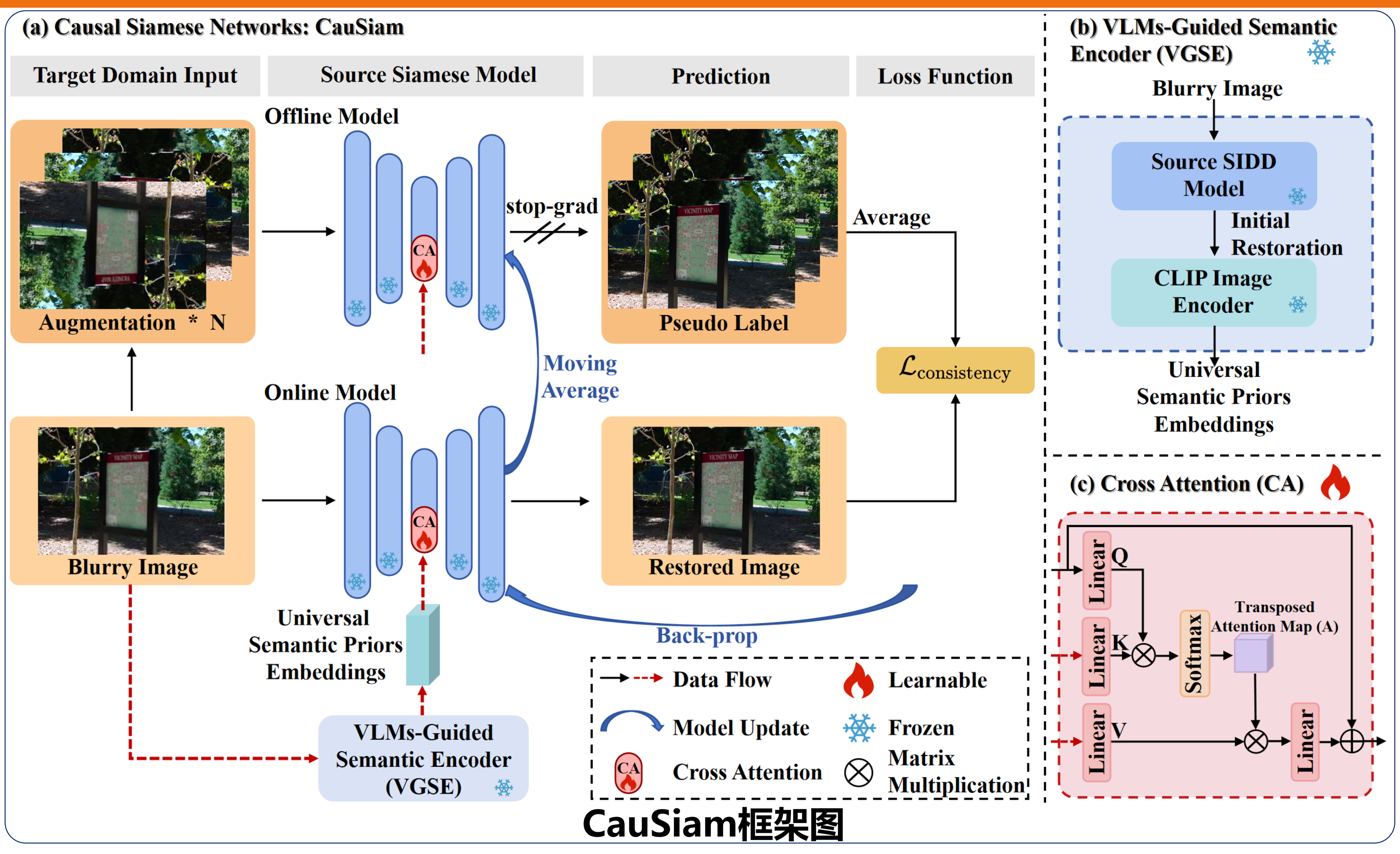
研究动机与贡献

- 问题挑战：图像散焦模糊去除（SIDD）在分布外(OOD)场景泛化受限，核心源于训练-测试数据的分布偏移。
- 贡献1 (**根源剖析**)：首次揭示镜头PSF异质性是加剧SIDD模型OOD性能下降的关键内因（动机实验充分支撑）。
- 贡献2 (**适应框架**)：首创SIDD领域持续测试时适应(CTTA)框架，有效缓解镜头PSF异质性导致的训练-测试分布偏移。
- 贡献3 (**因果增强**)：基于SCM分析，提出CauSiam框架，创新融合VLMs通用语义先验，消除语义错误纹理，保障模糊输入-恢复结果的因果可识别性。
- 贡献4 (**实验验证**)：五个数据集验证CauSiam显著提升源模型性能与泛化性。

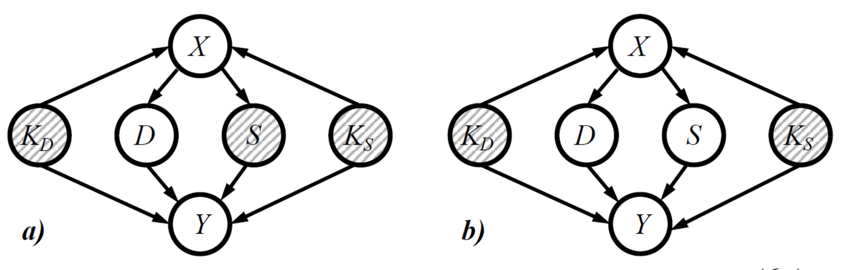
动机实验



提出的方法



CauSiam框架图



$$P(y|do(x)) \tag{6a}$$

$$= \sum_{k_d}\sum_{k_s}\sum_{d}\sum_{s} P(k_d)P(k_s)P(d|x)P(s|x)P(y|k_d,k_s,d,s) \tag{6b}$$

$$= \sum_{k_d}\sum_{k_s}\sum_{d}\sum_{s} P(k_d,k_s)P(d|x)P(s|x)P(y|k_d,k_s,d,s) \tag{6c}$$

$$= \sum_{k_d}\sum_{k_s}\sum_{d}\sum_{s}\sum_{x'} P(k_d,k_s|x')P(x')P(d|x)P(s|x) P(y|k_d,k_s,d,s) \tag{6d}$$

$$= \sum_{k_d}\sum_{k_s}\sum_{d}\sum_{s}\sum_{x'} P(k_d,k_s|x',d,s)P(x')P(d|x)P(s|x) P(y|k_d,k_s,d,s) \tag{6e}$$

$$= \sum_{k_d}\sum_{k_s}\sum_{d}\sum_{s}\sum_{x'} P(k_d,k_s|x',d,s)P(y|k_d,k_s,d,s,x') P(d|x)P(s|x)P(x') \tag{6f}$$

$$= \sum_{d}\sum_{s}\sum_{x'} P(y|d,s,x')P(d|x)P(s|x)P(x'), \tag{6g}$$

SIDD结构因果模型图和可识别性推导

CauSiam框架

面向跨设备单张离焦图像去模糊 (SIDD)，解决镜头PSF异质性引起的分布偏移。

- SiamCTTA (孪生网络持续自适应): 基于**孪生网络** (在线/离线协同优化 + 增广一致性损失 + 滑动平均)，实现模型持续适配新设备，缓解遗忘。
- CSPI (因果语义先验集成): 利用**预训练VLM的通用知识**，通过 VGSE (语义编码) 和 CA (语义融合)，注入语义先验以保障恢复结果的因果可识别性。

Algorithm 1: CauSiam algorithm for SIDD during CTTA.

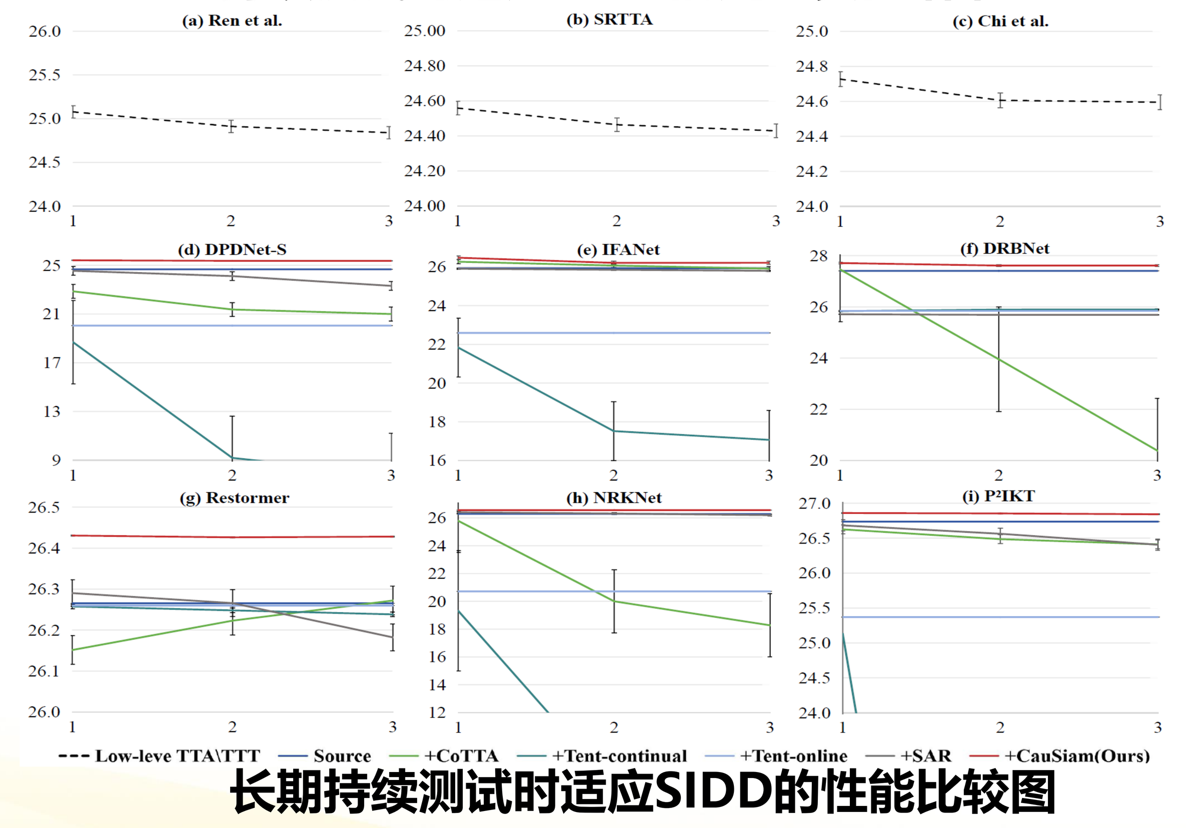
Input: A source SIDD model $\mathcal{F}_{\zeta}$; for time step t, the current single test sample x^t_{test}; hyper-parameters (e.g., iteration number K).
Output: Adapted prediction y_{mean}; updated online model $\mathcal{F}_{\theta}$; updated offline model $\mathcal{F}_{\xi}$.

for i=1 *to* K **do**
  Integrate causality-driven semantic priors into the source SIDD model to generate the online model $\mathcal{F}_{\theta}$ and the offline model $\mathcal{F}_{\xi}$. Initialize these models using the source SIDD model $\mathcal{F}_{\zeta}$;
  Augment the test sample and obtain the averaged pseudo label y_{mean} from the offline model $\mathcal{F}_{\xi}$ by Equation (2);
  Update the online model $\mathcal{F}_{\theta}$ using the consistency loss in Equation (4);
  Update the offline model $\mathcal{F}_{\xi}$ by exponential moving average in Equation (5).
end

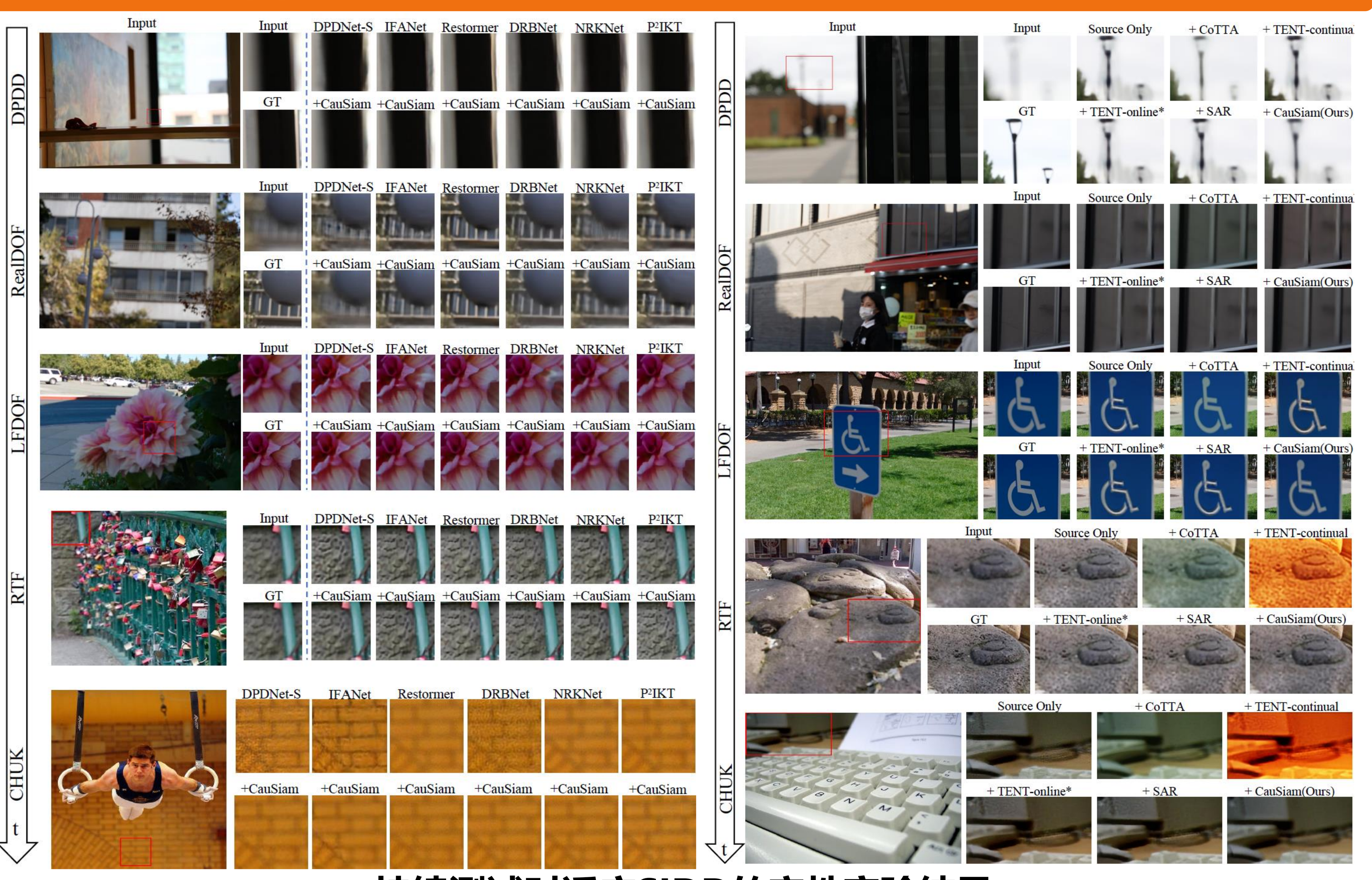
实验结果

Time	t →									
Method	DPDD PSNR	DPDD SSIM	RealDOF PSNR	RealDOF SSIM	LFDOF PSNR	LFDOF SSIM	RTF PSNR	RTF SSIM	Average PSNR↑	Average SSIM↑
Ren et al. (Ren et al. 2020)	23.686	0.725	22.259	0.629	25.459	0.765	23.728	0.751	25.078	0.753
SRTTA (Deng et al. 2023)	24.442	0.735	22.376	0.640	24.739	0.757	23.990	0.740	24.559	0.748
Chi et al. (Chi et al. 2021)	24.166	0.731	22.244	0.638	24.993	0.757	23.556	0.718	24.727	0.747
GGKMNet (Quan et al. 2024)	26.039	0.806	24.942	0.763	—	—	25.895	0.827	—	—
GGKMNet† (Quan et al. 2024)	26.272	0.810	25.355	0.770	—	—	26.012	0.846	—	—
DPDNet-S (Abuolaim and Brown 2020)	24.648	0.758	23.254	0.686	24.810	0.768	23.578	0.757	24.676	0.762
+ CoTTA (Wang et al. 2022a)	24.633	0.754	22.439	0.650	22.746	0.727	21.583	0.685	22.863	0.724
+ TENT-continual (Wang et al. 2021)	24.590	0.758	23.083	0.685	18.002	0.693	11.013	0.549	18.690	0.695
+ TENT-online* (Wang et al. 2021)	24.590	0.758	23.240	0.686	19.244	0.715	23.569	0.757	20.047	0.718
+ SAR (Niu et al. 2023)	24.646	0.758	23.248	0.686	24.663	0.768	23.366	0.758	24.548	0.762
+ CauSiam(Ours)	**24.862**	**0.759**	**23.713**	**0.687**	**25.617**	**0.778**	**24.399**	**0.785**	**25.412**	**0.774**
Ours Gains	+0.214	+0.001	+0.459	+0.001	+0.807	+0.010	+0.821	+0.028	+0.736	+0.012
IFANet (Lee et al. 2021)	25.364	0.788	24.707	0.748	26.107	0.816	24.926	0.821	25.932	0.810
+ CoTTA (Wang et al. 2022a)	25.704	**0.795**	25.102	0.758	26.434	0.821	25.489	0.825	26.270	0.815
+ TENT-continual (Wang et al. 2021)	25.313	0.788	24.672	0.749	21.420	0.746	17.211	0.597	21.839	0.746
+ TENT-online* (Wang et al. 2021)	25.313	0.788	24.685	0.748	22.090	0.739	24.899	0.821	22.590	0.746
+ SAR (Niu et al. 2023)	25.363	0.788	24.707	0.748	26.077	0.816	24.888	0.821	25.907	0.810
+ CauSiam(Ours)	**25.756**	**0.795**	**25.204**	**0.762**	**26.661**	**0.825**	**25.804**	**0.837**	**26.478**	**0.819**
Ours Gains	+0.392	+0.007	+0.497	+0.014	+0.554	+0.008	+0.878	+0.016	+0.546	+0.009
DRBNet (Ruan et al. 2022)	25.722	0.791	25.743	0.770	27.737	0.836	26.221	0.853	27.409	0.829
+ CoTTA (Wang et al. 2022a)	**25.754**	**0.793**	25.864	0.773	27.795	0.835	26.121	0.837	27.464	0.828
+ TENT-continual (Wang et al. 2021)	24.241	0.757	22.247	0.696	26.258	0.809	25.606	0.846	25.836	0.799
+ TENT-online* (Wang et al. 2021)	24.241	0.757	23.117	0.711	26.206	0.813	25.711	0.840	25.846	0.803
+ SAR (Niu et al. 2023)	24.237	0.757	22.200	0.695	26.117	0.807	25.484	0.844	25.713	0.797
+ CauSiam(Ours)	25.750	**0.793**	**25.865**	**0.777**	**28.085**	**0.843**	**26.476**	**0.861**	**27.714**	**0.835**
Ours Gains	+0.028	+0.002	+0.122	+0.007	+0.348	+0.007	+0.255	+0.008	+0.305	+0.006

持续测试时适应SIDD的定量实验结果



长期持续测试时适应SIDD的性能比较图



持续测试时适应SIDD的定性实验结果

Time					t →									
Method	VSPI	L_s	L_f	CA_{only}	EMA	DPDD PSNR	DPDD SSIM	RealDOF PSNR	RealDOF SSIM	LFDOF PSNR	LFDOF SSIM	RTF PSNR	RTF SSIM	Average PSNR↑	Average SSIM↑
(a)						24.648	0.758	23.254	0.686	24.810	0.768	23.578	0.757	24.676	0.762
(b)	✗	✓	✓	✓	✓	**24.984**	**0.766**	23.711	0.686	25.209	0.776	24.148	0.779	25.077	0.770
(c)	✓	✗	✓	✓	✓	24.390	0.752	23.274	0.679	25.114	0.766	23.729	0.761	24.910	0.760
(d)	✓	✓	✗	✓	✓	24.782	0.755	23.513	0.682	25.606	0.775	24.395	**0.785**	25.384	0.768
(e)	✓	✓	✓	✗	✓	24.457	0.740	22.959	0.663	25.402	0.777	24.072	0.769	25.146	0.767
(f)	✓	✓	✓	✓	✗	24.350	0.748	23.125	0.675	25.605	**0.779**	24.398	**0.785**	25.323	0.770
(g)	✓	✓	✓	✓	✓	24.862	0.759	**23.713**	**0.687**	**25.617**	0.778	**24.399**	**0.785**	**25.412**	**0.771**

消融实验结果

- 现有散焦模糊去除以及其他持续测试时适应方法相比，所提出的因果孪生网络（CauSiam）在多个数据集均取得**领先性能**，有效实现高保真重建和抑制伪影，确保复原后图像可靠性