Visible Watermark Removal via Self-calibrated Localization and Background Refinement

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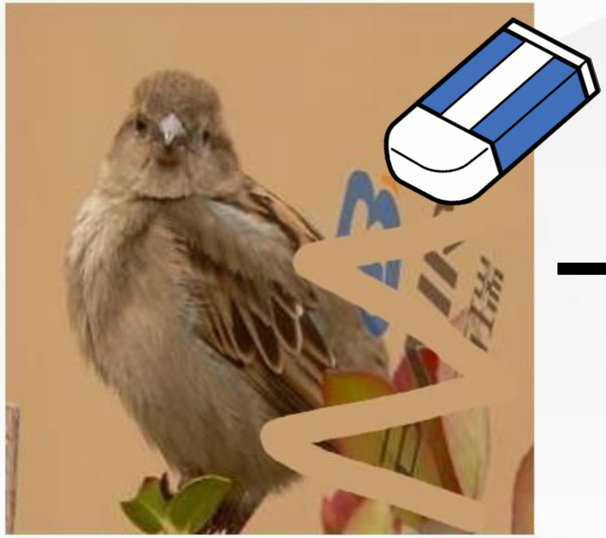
1. Background—What is Watermark Removal?

Watermarked Image



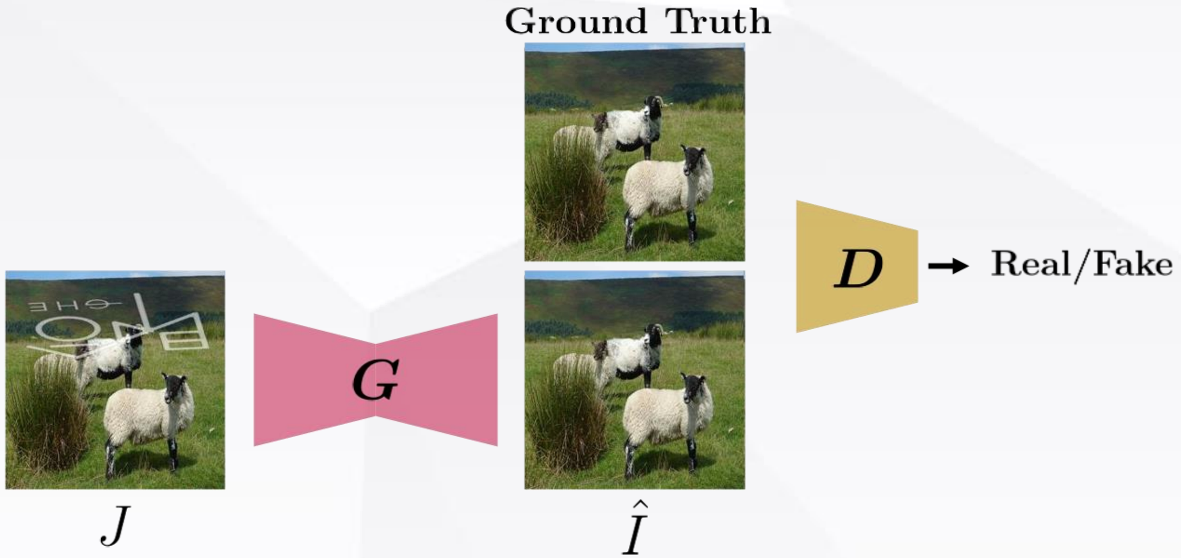
Erasing

Watermarked-free Image

1. Challenges

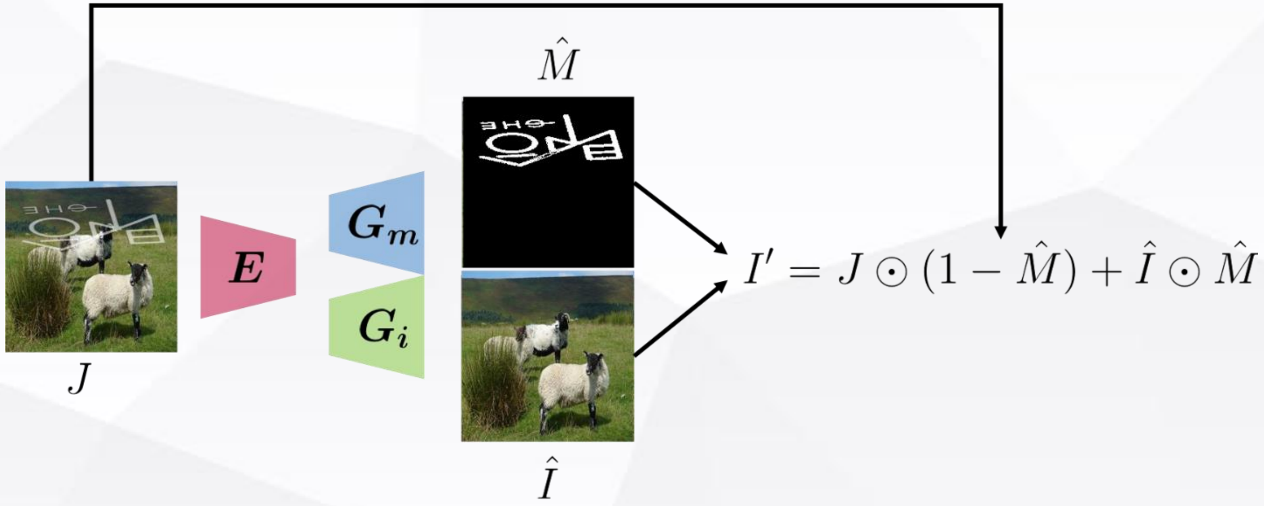
Watermarked Image | Mask GT | Background Prediction | Mask Prediction

1. Previous Works



A. Image-to-image Translation Problem[1][2]

B. Multi-task Learning Problem[3][4]



[1] Zhiyi Cao, Shaozhang Niu, Jiwei Zhang, and Xinyi Wang. Generative adversarial networks model for visible watermark removal. In IET Image Processing 2019.
[2] Xiang Li, Chan Lu, Danni Cheng, Wei-Hong Li, Mei Cao, Bo Liu, Jiechao Ma, and Wei-Shi Zheng. Towards photo-Realistic visible watermark removal with conditional generative adversarial networks. In International Conference on Image and Graphics 2019.
[3] Amir Hertz, Sharon Fogel, Rana Hanocka, Raja Giryes, and Daniel Cohen. Blind visual motif removal from a single image. In CVPR 2019.
[4] Yang Liu, Zhen Zhu, and Xiang Bai. WDNet: watermark-decomposition network for visible watermark removal. In WACV 2021.

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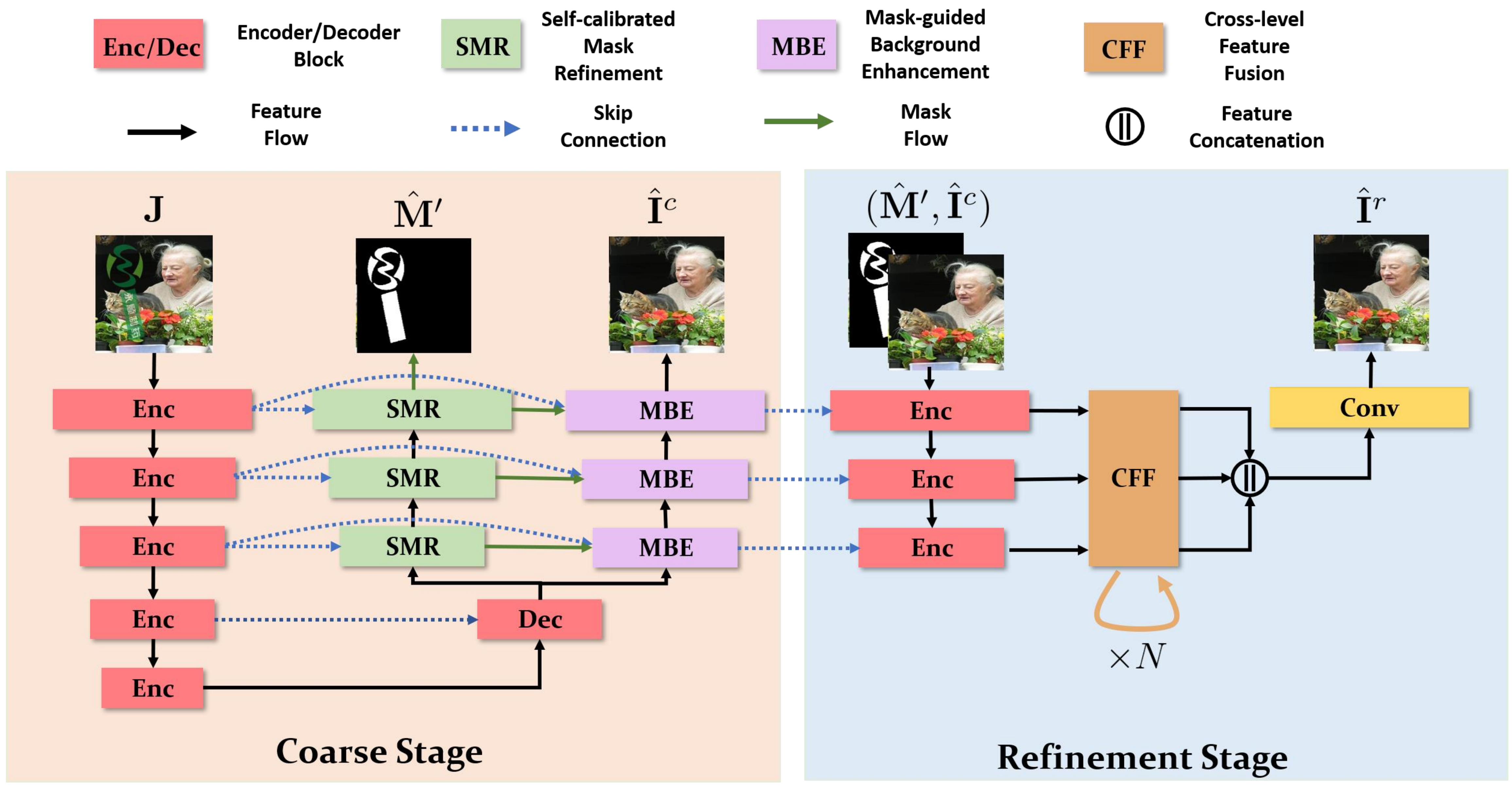
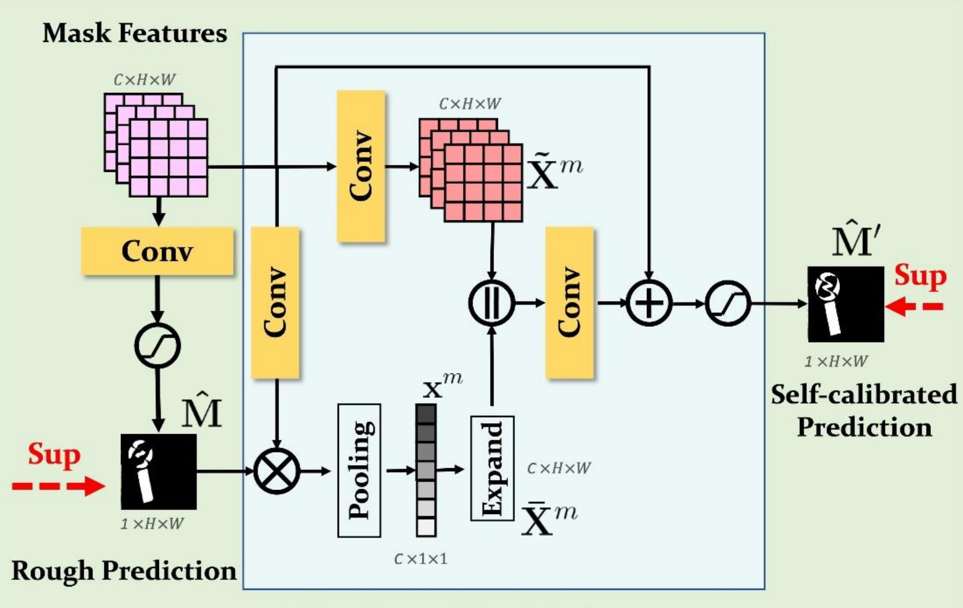
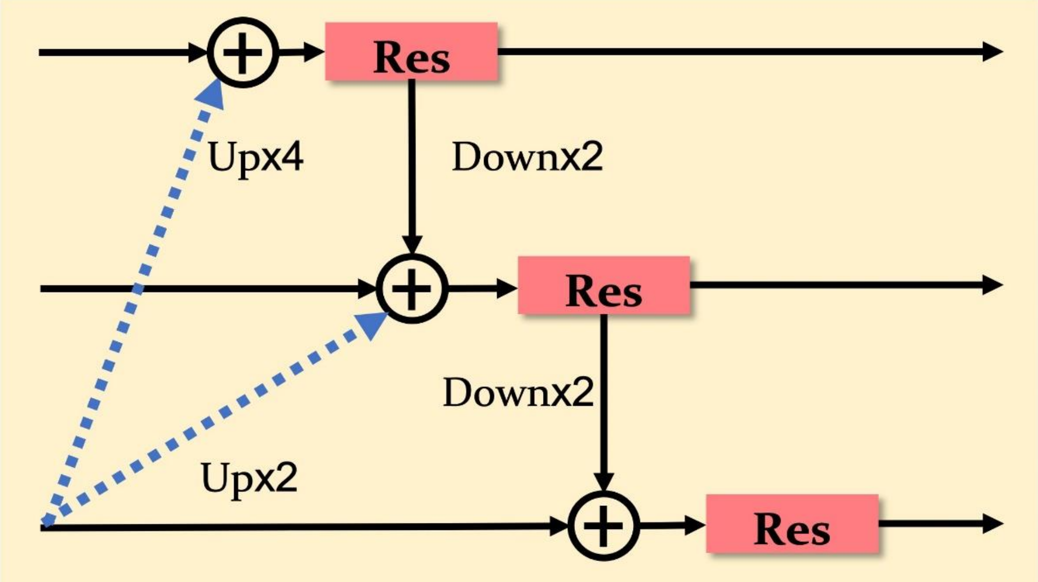
2. Methods—SLBR



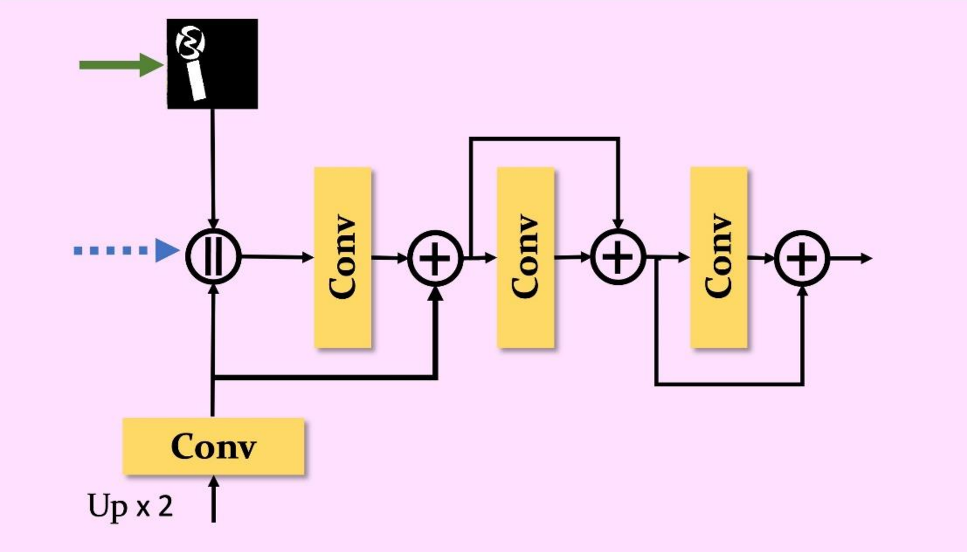
2. Methods—SLBR



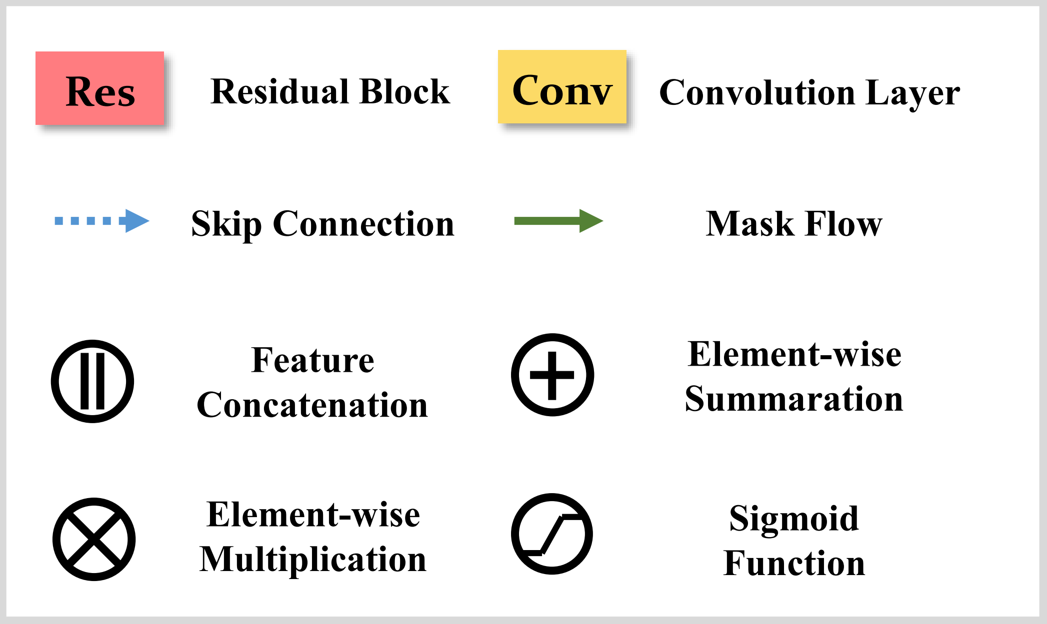
Self-calibrated Mask Refinement



Cross-layer Feature Fusion



Mask-guided Background Enhancement



2. Methods—SLBR

➢ Loss functions:

- **Localization losses:**

$$\mathcal{L}_{mask} = -\sum_{i,j}\left(M_{i,j}\log \hat{M}_{i,j} + (1 - M_{i,j})\log(1 - \hat{M}_{i,j})\right)$$

$$\mathcal{L}'_{mask} = -\sum_{i,j}\left(M_{i,j}\log \hat{M}'_{i,j} + (1 - M_{i,j})\log(1 - \hat{M}'_{i,j})\right)$$

$$+1 - \frac{\sum_{i,j} M_{i,j}\cdot \hat{M}_{i,j}}{\sum_{i,j} M_{i,j} + \sum_{i,j}\hat{M}_{i,j} - \sum_{i,j} M_{i,j}\cdot \hat{M}_{i,j}}$$

- **Reconstruction losses:**

$$\mathcal{L}^{c}_{bg-L_1} = \|\mathbf{I} - \hat{\mathbf{I}}^{c}\|_1$$

$$\mathcal{L}^{r}_{bg-L_1} = \|\mathbf{I} - \hat{\mathbf{I}}^{r}\|_1$$

$$\mathcal{L}_{bg-vgg} = \sum_{k\in 1,2,3}\|\Phi^{k}_{vgg}(\hat{\mathbf{I}}^{r}) - \Phi^{k}_{vgg}(\mathbf{I})\|_1$$

- **Total loss:**

$$\mathcal{L}_{all} = \mathcal{L}^{c}_{bg-L_1} + \mathcal{L}^{r}_{bg-L_1} + \lambda_{\mathrm{vgg}}\mathcal{L}_{bg-vgg} + \lambda_{\mathrm{mask}}(\mathcal{L}_{\mathrm{mask}} + \mathcal{L}'_{\mathrm{mask}}),$$

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3. Experiments

We conduct all experiments on the LVW dataset and the CLWD dataset.

LVW

Watermarked Image | Watermarked-free Image | Mask Ground Truth

Training set: 48,000 made of 64 gray-scale watermarks
Test set: 12,000 made of 16 gray-scale watermarks

CLWD

Watermarked Image | Watermarked-free Image | Mask Ground Truth

Training set: 60,000 made of 160 colored watermarks
Test set: 10,000 made of 40 colored watermarks

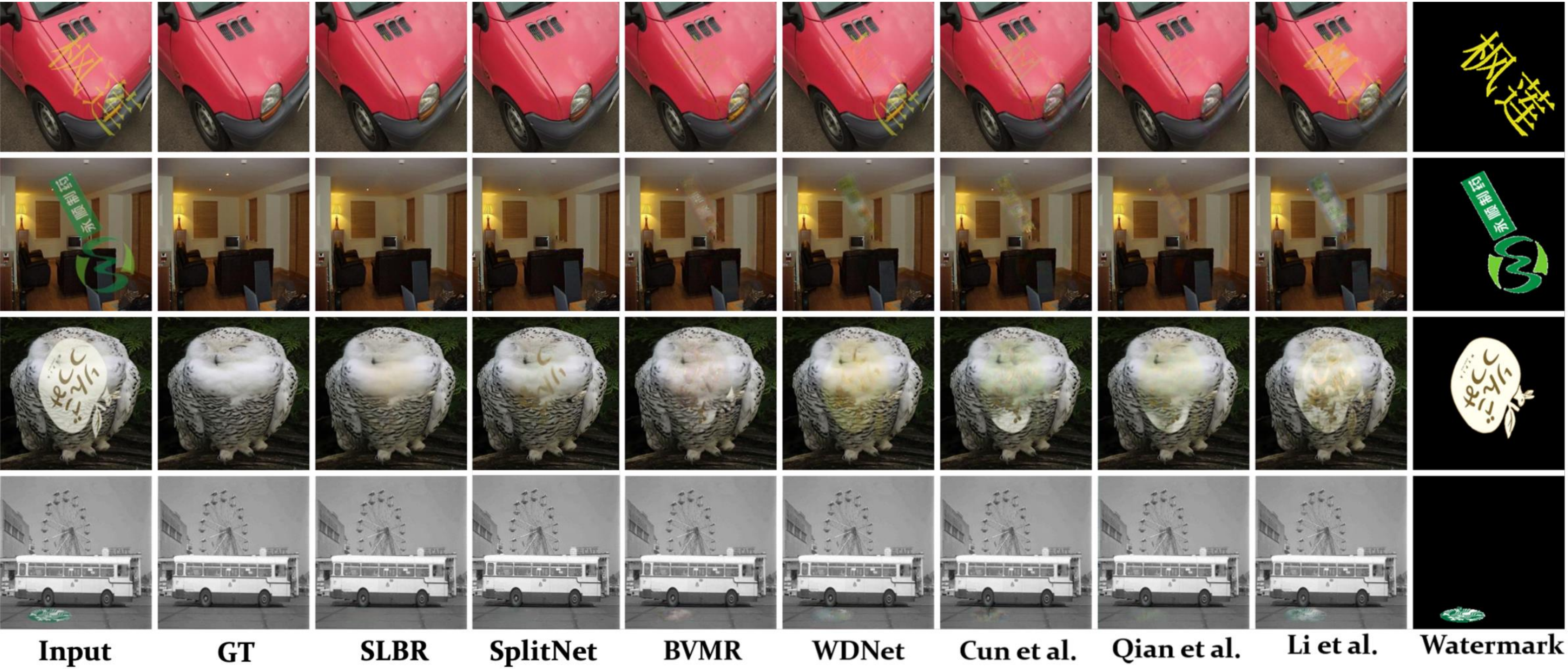
$$\mathrm{Watermark}_{\mathrm{train}} \cap \mathrm{Watermark}_{\mathrm{test}} = \emptyset$$

3. Experiments—Quantitative Comparisons

Method	LVW				CLWD			
	PSNR ↑	SSIM ↑	RMSE ↓	RMSEw ↓	PSNR ↑	SSIM ↑	RMSE ↓	RMSEw ↓
U-Net [33]	30.33	0.9517	7.11	42.18	23.21	0.8567	19.35	48.43
Qian *et al.* [32]	39.92	0.9902	3.31	21.40	34.60	0.9694	5.40	19.34
Cun *et al.* [7]	40.68	0.9949	2.62	17.29	35.29	0.9712	5.28	18.25
Li *et al.* [24]	33.57	0.9690	5.84	34.71	27.96	0.9161	12.63	46.80
Cao *et al.* [2]	34.16	0.9714	5.51	33.42	29.04	0.9363	10.36	41.21
WDNet [28]	42.45	0.9954	2.39	12.75	35.53	0.9738	5.11	17.27
BVMR [19]	40.14	0.9910	3.24	18.57	35.89	0.9734	5.02	18.71
SplitNet [6]	43.16	0.9946	2.28	14.06	37.41	0.9787	4.23	15.25
SLBR (Ours)	**43.48**	**0.9959**	**2.15**	**12.14**	**38.28**	**0.9814**	**3.76**	**14.07**

Table 1: The results of different methods on LVW [4] and CLWD [28] datasets. The best results are denoted in boldface.

3. Experiments—Qualitative Comparisons



3. Experiments--Watermark Localization

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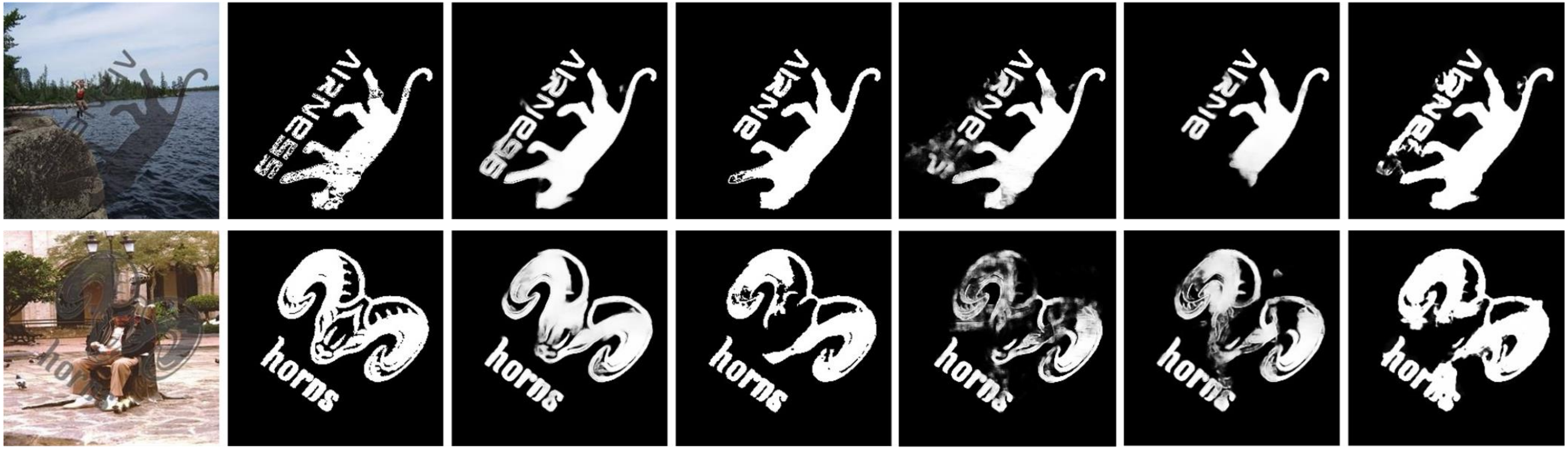

Method	Evaluation Metrics	
	F1	IoU (%)
BVMR [19]	0.7871	70.21
WDNet [28]	0.7240	61.20
SplitNet [6]	0.8027	71.96
SLBR ($\hat{\mathrm{M}}$)	0.8107	73.10
SLBR ($\hat{\mathrm{M}}'$)	**0.8234**	**74.63**

Thank You!

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