Visible Watermark Removal with Dynamic Kernel and Semantic-aware Propagation

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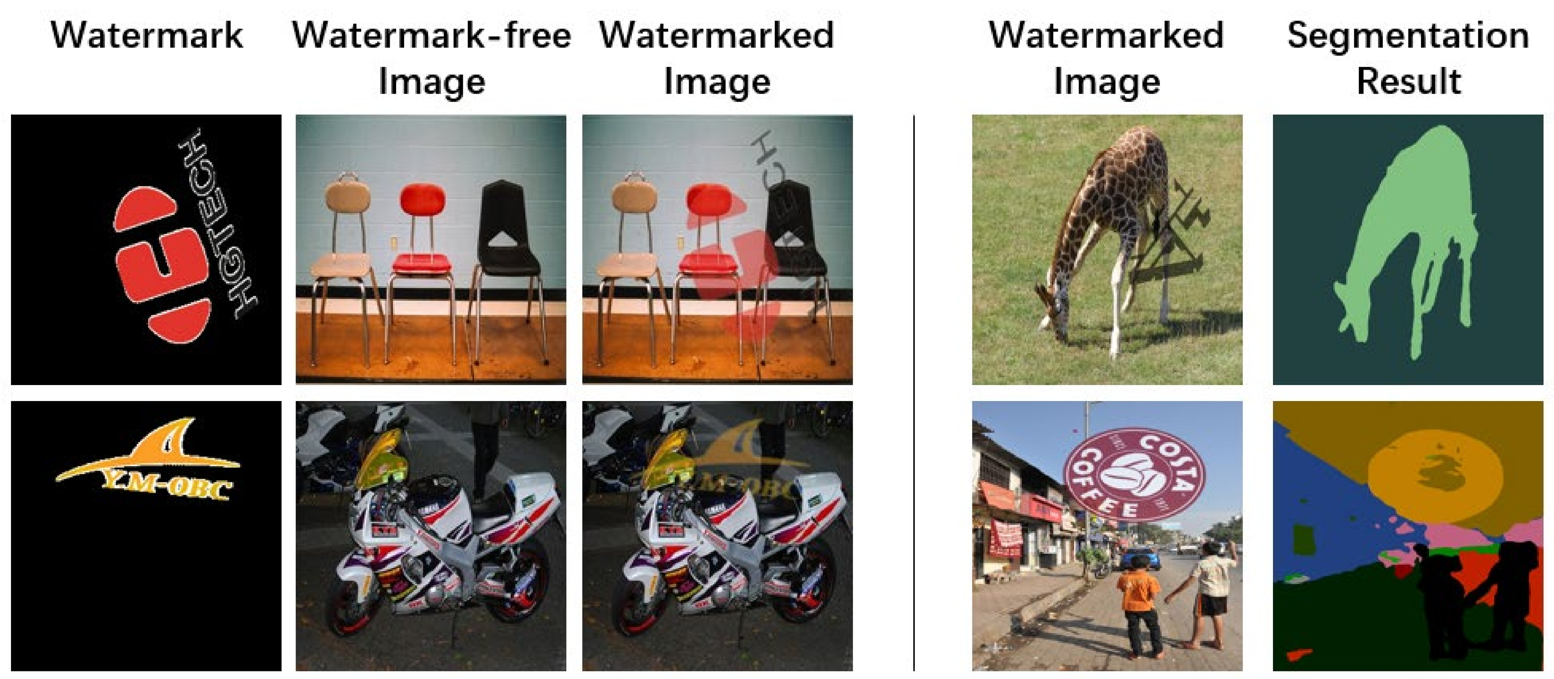
Introduction

As a prevalent information carrier nowadays, images are ubiquitous in a wide range of applications, during which the copyright issue becomes critical for information security. To solve this problem, we can superimpose visible watermarks on images to clarify and protect the copyright. As an inverse process, visible watermark removal aims to erase the visible watermark and reconstruct the background image.



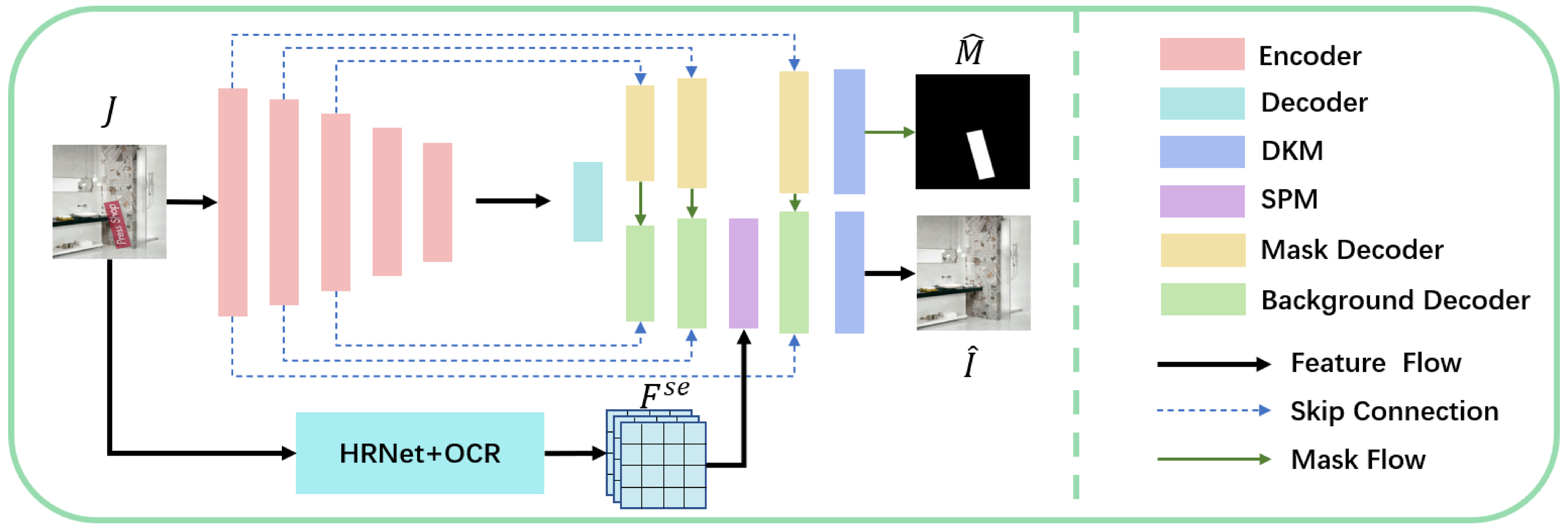
- **Dynamic kernel**: Dynamically generate the convolutional kernel according to the watermark feature, so that the network can adaptively cope with different types of watermarks.
- **Semantic-aware propagation**: When using pretrained segmentation model to segment a watermarked image, we observe that the segmentation model usually ignores the watermark region, or classifies the watermark region as an isolated object. In either case, it is useful to transfer information from semantically similar pixels in the neighboring region to the watermarked pixels.

Conclusion

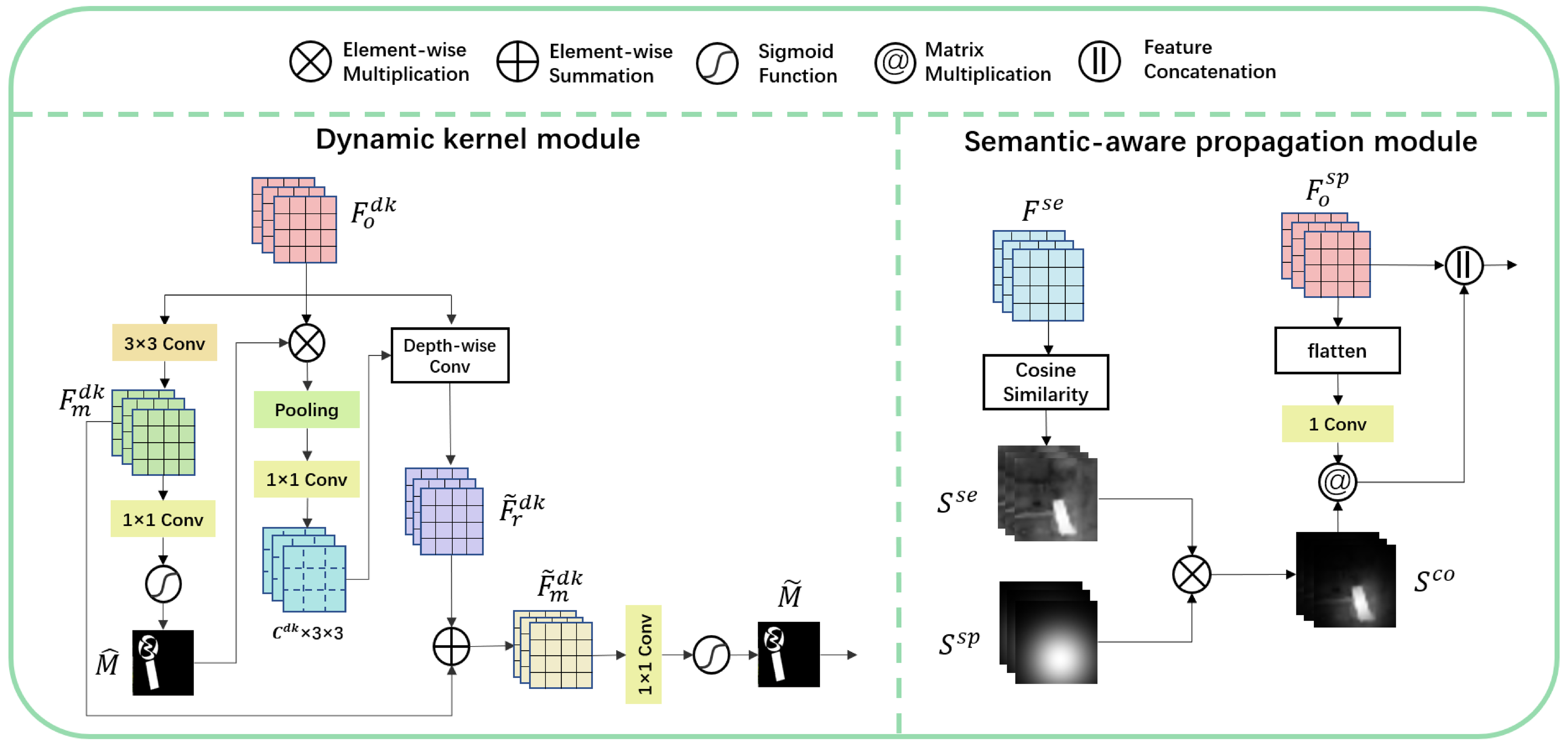
we concentrate on watermark removal and develop a U-Net like model that incorporates a novel Dynamic Kernel Module and Semantic-aware Propagation Module, which can simultaneously predict watermark masks and reconstruct watermark-free images.

Method

Our DKSP mainly consists of a U-Net architecture, which includes a shared encoder and two decoders responsible for watermark localization (mask decoder) and background image reconstruction (background decoder) respectively. In the two decoders, we insert additional modules to enhance the performance. Specifically, we insert dynamic kernel module (DKM) to both decoders, and insert semantic-aware propagation module (SPM) to the background decoder. The required semantic information in SPM is provided by an off-the-shelf HRNet+OCR model pretrained on COCO-Stuff dataset.



- **Dynamic kernel**: Extract the features of the watermark according to the generated rough mask, and generate a dynamic convolution kernel based on this.
- **Semantic-aware propagation**: Use semantic features generated by the off-the-shelf segmentation model as semantic similarity map, then multiply with the spatial similarity map as the total similarity map, which is used to propagate the information within the images.



Results

Quantitative Comparison

Main results

Method	CLWD				LOGO30K			
	PSNR↑	$RMSE_w$ ↓	IoU(%)↑	F_1 ↑	PSNR↑	$RMSE_w$ ↓	IoU(%)↑	F_1 ↑
U-Net [34]	23.21	48.43	-	-	24.64	43.29	-	-
Qian *etal*. [33]	34.60	19.34	56.65	0.6910	36.89	17.26	62.68	0.7565
Cun *etal*. [7]	35.29	18.25	59.41	0.7122	37.67	16.88	65.13	0.7745
Li *etal*. [25]	27.96	46.80	-	-	30.51	39.11	-	-
Cao *etal*. [2]	29.04	41.21	-	-	32.18	35.16	-	-
WDNet [28]	35.53	17.27	61.20	0.7240	39.15	15.94	68.21	0.8010
BVMR [19]	35.89	18.71	70.21	0.7871	38.28	16.72	72.87	0.8305
SplitNet [6]	37.41	15.25	71.96	0.8027	41.27	14.85	74.14	0.8411
SLBR [26]	38.28	14.07	74.63	0.8234	41.50	14.69	78.58	0.8647
DKSP	**38.84**	**12.16**	**77.30**	**0.8480**	**42.16**	**13.78**	**80.16**	**0.8770**

Ablation study

#	DKM	SPM	Evaluation Metrics			
			PSNR↑	$RMSE_w$ ↓	IoU(%)↑	F_1 ↑
1	-	-	38.23	16.90	73.56	0.8308
2	w/o residual output	-	38.90	16.43	78.69	0.8634
3	w/o $\hat{M}$ mul	-	38.88	16.54	76.58	0.8521
4	SMR [26]	-	38.94	15.99	79.15	0.8678
5	√	-	39.41	15.90	79.71	0.8707
6	√	self-attention [39]	39.97	15.21	79.82	0.8725
7	√	w/o S^{se}	39.90	15.59	79.81	0.8721
8	√	w/o S^{sp}	41.66	14.36	80.14	0.8748
9	√	√	**42.16**	**13.78**	**80.16**	**0.8770**

Qualitative Comparison

Watermark-free images produced by various methods

Predicted masks of various method