DRT: A Lightweight Single Image Deraining Recursive Transformer

Yuanchu Liang[1], Saeed Anwar[1,2], Yang Liu[1]

The Australian National University, Data61-CSIRO

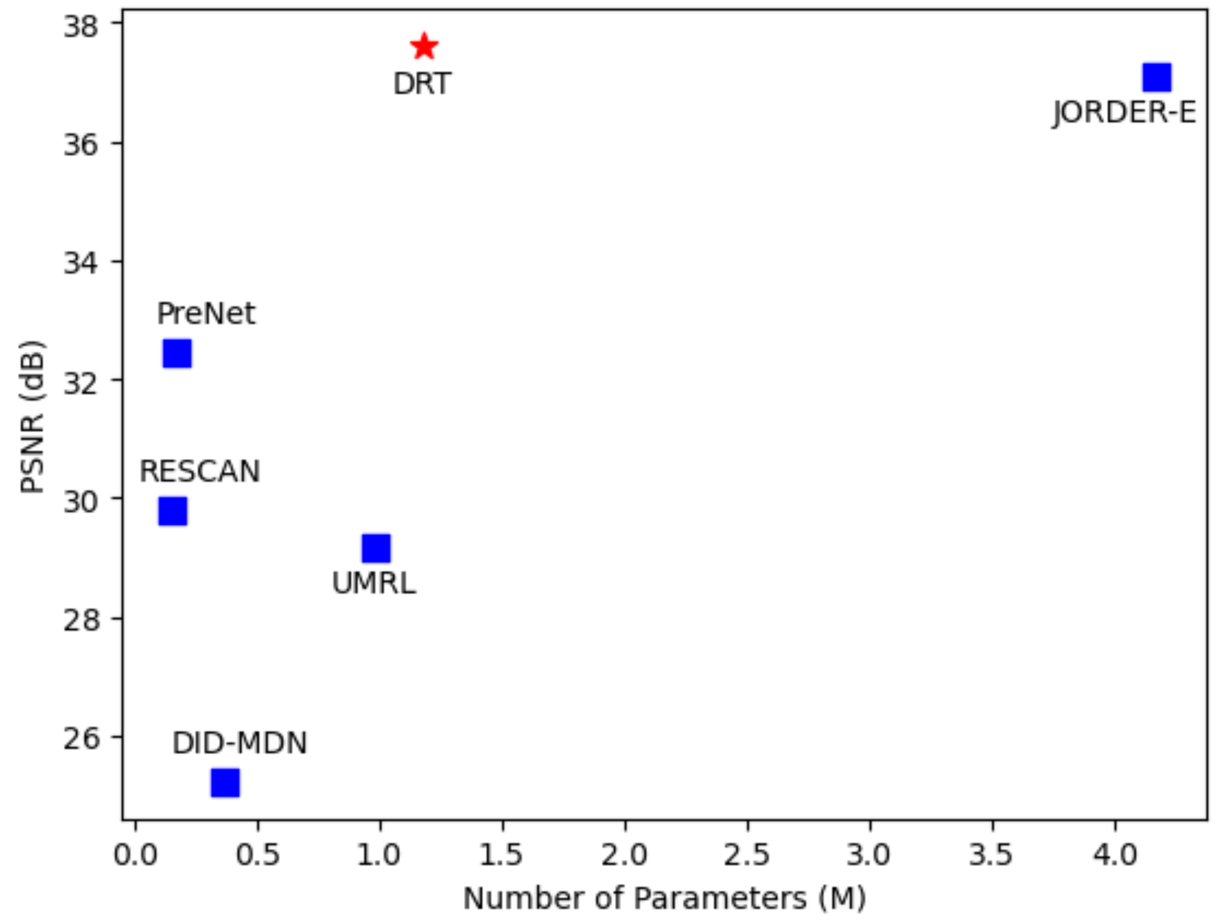
Summary:

We introduce a Deraining Recursive Transformer (DRT) with local window-based self-attention structure and residual connections, which enjoys the superiority of the transformer but consumes little computing resources.

Background:

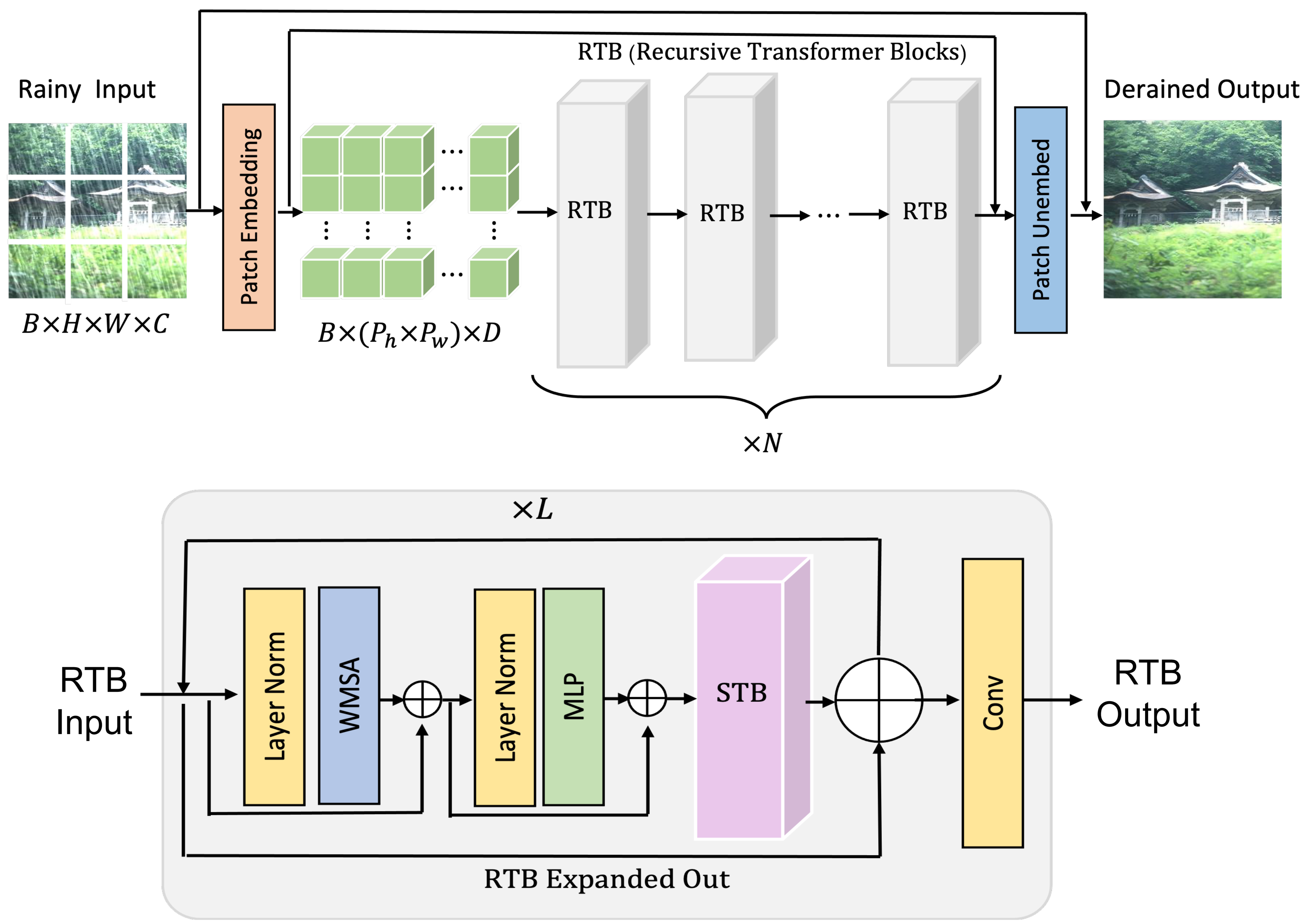
The problem of single image deraining aims to take a rainy image (I) as input and apply a function (f) to reconstruct the background image $(\hat{I} = f(I))$ without any rain streaks. Recently, this function is usually learnt by a deep learning model.

Motivation:



Deraining methods using the transformer as the backbone structure achieve superior performance comparing to CNN based methods. However, these new methods typically require a lot of computing resources. Is there a transformer based models that can achieve excellent deraining performance while requiring less computing power and memory?

Deraining Recursive Transformer (DRT)



- The network firstly embeds the input image into appropriate patches for the main inference channel (the sequence of the RTBs) to perform deraining. The processed patches from the channel are then resembled to form the full residual image.
- Each RTB consists of two residually connected Swin Transformer Blocks (STBs) and these two blocks are recursively called multiple times to reduce memory usage and boost efficiency.
- There is a convolution layer without any activation function at the end of the each RTB to process location information which maybe ignored by the STB.

Quantitative Results:

- Exceeding previous methods by 0.33db on the Rain100L data set.
- Use ~1.3% of the number of parameters compare to the previous best performing method.

Methods	Test100		Rain100L		Rain100H		Params (M)
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	
Ideal	∞	1	∞	1	∞	1	–
HiNet [4]	30.29	0.906	37.28	0.97	30.65	0.894	88.7
DerainNet [8]	22.77	0.810	27.03	0.884	14.92	0.592	–
JORDER [23]	21.09	0.753	36.61	0.974	26.54	0.835	–
JORDER-E [22]	27.08	0.872	37.10	0.979	24.54	0.802	4.17
SEMI [21]	22.35	0.788	25.03	0.842	16.56	0.486	–
DIDMDN [27]	22.56	0.818	25.23	0.741	17.35	0.524	0.372
UMRL [26]	24.41	0.829	29.18	0.923	26.01	0.832	0.984
RESCAN [12]	25.00	0.835	29.80	0.881	26.36	0.786	0.150
PreNet [17]	24.81	0.851	32.44	0.950	26.77	0.858	0.169
DRT (Ours)	**27.02**	**0.847**	**37.61**	**0.948**	**29.47**	**0.846**	**1.18**

Qualitative Results: