Magic ELF: Image Deraining Meets Association Learning and Transformer

Kui Jiang  
NERCMS, Wuhan University, China

Zhongyuan Wang∗  
NERCMS, Wuhan University, China

Chen Chen  
CRCV, University of Central Florida U.S.

Zheng Wang∗  
NERCMS, Wuhan University, China

Laizhong Cui  
Shenzhen University, China

Chia-Wen Lin  
National Tsing Hua University, China

ABSTRACT
Convolutional neural network (CNN) and Transformer have achieved great success in multimedia applications. However, little effort has been made to effectively and efficiently harmonize these two architectures to satisfy image deraining. This paper aims to unify these two architectures to take advantage of their learning merits for image deraining. In particular, the local connectivity and translation equivariance of CNN and the global aggregation ability of self-attention (SA) in Transformer are fully exploited for specific local context and global structure representations. Based on the observation that rain distribution reveals the degradation location and degree, we introduce degradation prior to help background recovery and accordingly present the association refinement deraining scheme. A novel multi-input attention module (MAM) is proposed to associate rain perturbation removal and background recovery. Moreover, we equip our model with effective depth-wise separable convolutions to learn the specific feature representations and trade off computational complexity. Extensive experiments show that our proposed method (dubbed as ELF) outperforms the state-of-the-art approach (MPRNet) by 0.25 dB on average, but only accounts for 11.7% and 42.1% of its computational cost and parameters.

CCS CONCEPTS
• Computing methodologies → Computer vision; Machine learning algorithms.

KEYWORDS
Image Deraining, Self-attention, Association Learning

1 INTRODUCTION
Rain perturbation causes detrimental effects on image quality and significantly degrades the performance of multimedia applications like image understanding [33, 47], object detection [66] and identification [52]. Image deraining [5, 20, 44] tends to produce the rain-free result from the rainy input, and has drawn widespread attention in the last decade. Prior to deep neural networks, the early model-based deraining methods [12] rely more on statistical analyses of image contents, and enforce handcrafted priors (e.g., sparsity and non-local means filtering) on both rain and background. Still, they are not robust to varying and complex rain conditions [2, 6, 65].

Because of the powerful ability to learn generalizable priors from large-scale data, CNNs have emerged as a preferable choice compared to conventional model-based methods. To further promote the deraining performance, various sophisticated architectures and training practices are designed to boost the efficiency and generalization [17, 55, 55, 57]. However, due to intrinsic characteristics of local connectivity and translation equivariance, CNNs have at least two shortcomings: 1) limited receptive field; 2) static weight of sliding window at inference, unable to cope with the content diversity. The former thus prevents the network from capturing the long-range pixel dependencies while the latter sacrifices the adaptability to the input contents. As a result, it is far from meeting the requirement in modeling the global rain distribution, and generates results with obvious rain residue (Prenet [40] and DRDNet [18]) or detail loss (MPRNet [59] and SWAL [14]). Please refer to the region highlighted in the red boxes for a close up comparison.
Self-attention (SA) calculates response at a given pixel by a weighted sum of all other positions, and thus has been explored in deep networks for various natural language and computer vision tasks [43, 49, 60]. Benefitting from the advantage of global processing, SA achieves significant performance boost over CNNs in eliminating the degradation perturbation [4, 32, 51]. However, due to the global calculation of SA, its computation complexity grows quadratically with the spatial resolution, making it infeasible to apply to high-resolution images [58]. More recently, Restormer [58] proposes a multi-Dconv head "transposed" attention (MDTA) block to model global connectivity, and achieves impressive deraining performance. Although MDTA applies SA across feature dimension rather than the spatial dimension and has linear complexity, still, Restormer quickly overtaxes the computing resources. As illustrated in Figure 2, the high-accuracy model Restormer [58] requires much more computation resource for a better restoration performance. It has 563.96 GFlops and 26.10 Million parameters, and consumes 0.568s to derain an image with 512 x 512 pixels using one TITAN X GPU, which is computationally or memory expensive for many real-world applications with resource-constrained devices.

Besides low efficiency, there are at least another two shortcomings for Restormer [58]. 1) Regarding the image deraining as a simple rain streaks removal problem based on the additive model is debatable, since the rain streak layer and background layer are highly intertwined, where rain streaks destroy image contents, including the details, color, and contrast. 2) Constructing a pure Transformer-based framework is suboptimal, since SA is good at aggregating global feature maps but immature in learning local contexture relations which CNNs are skilled at. That in turn naturally raises two questions: (1) How to associate the rain perturbation removal and background recovery? (2) How to unify SA and CNNs efficiently for image deraining?

To answer the first question, we take inspiration from the observation that rain distribution reflects the degradation location and degree, in addition to the rain distribution prediction. Therefore, we propose to refine background textures with the predicted degradation prior in an association learning manner. As a result, we accomplish the image deraining by associating rain streak removal and background recovery, where an image deraining network (IDN) and a background recovery network (BRN) are specifically designed for these two subtasks. The key part of association learning is a novel multi-input attention module (MAM). It generates the degradation prior and produces the degradation mask according to the predicted rainy distribution. Benefitted from the global correlation calculation of SA, MAM can extract the informative complementary components from the rainy input (query) with the degradation mask (key), and then help accurate texture restoration.

An intuitive idea to deal with the second issue is to construct a unified model with the advantages of these two architectures. It has been demonstrated that the SA and standard convolution exhibit opposite behaviors but complementary [38]. Specifically, SA tends to aggregate feature maps with self-attention importance, but convolution diversifies them to focus on the local textures. Unlike Restormer equipped with pure Transformer blocks, we promote the design paradigm in a parallel manner of SA and CNNs, and propose a hybrid fusion network. It involves one residual Transformer branch (RTB) and one encoder-decoder branch (EDB). The former takes a few learnable tokens (feature channels) as input and stacks multi-head attention and feed-forward networks to encode global features of the image. The latter, conversely, leverages the multi-scale encoder-decoder to represent contexture knowledge. We propose a light-weight hybrid fusion block (HFB) to aggregate the outcomes of RTB and EDB to yield a final solution to the subtask. In this way, we construct our final model as a two-stage Transformer-based method, namely ELF, for single image deraining, which outperforms the CNN-based SOTA (MPRNet [59]) by 0.25dB on average, while saves 88.3% and 57.9% computational cost and parameters.

The main contributions of this paper are summarized as follows.

- To the best of our knowledge, we are the first to consider the high efficiency and compatibility of Transformer and CNNs for the image deraining task, and unify the advantages of SA and CNNs into an association learning-based network for rain perturbation removal and background recovery. This showcases an efficient and effective implementation of part-whole hierarchy.
- We design a novel multi-input attention module (MAM) to associate rain streaks removal and background recovery tasks elaborately. It significantly alleviates the learning burden while promoting the texture restoration.
- Comprehensive experiments on image deraining and detection tasks have verified the effectiveness and efficiency of our proposed ELF method. ELF surpasses MPRNet [59] by 0.25dB on average, while the latter suffers from 8.5x computational cost and 2.4x parameters.

2 RELATED WORK

Image deraining has achieved significant progress in innovative architectures and training methods in the last few years. Next, we briefly describe the typical models for image deraining and visual Transformer relative to our studies.

Figure 2: Comparison of mainstream deraining methods in terms of efficiency (inference time (ms) and computational cost (GFlops)) vs. performance (PSNR) on the TEST1200 dataset with image size of 512 × 512. Compared with the top-performing method Restormer [18], our ELF achieves comparable deraining performance (33.38dB vs. 33.19dB) while saving 88.0% inference time (ms) (125 vs. 568) and 88.4% computational cost (GFlops) (66.39 vs. 568). Our light-weight model ELF-LW is still competitive, surpassing the real-time deraining method PCNet by 0.52dB while with less computation cost (GFlops) (21.53 vs. 28.21).

| Method          | PSNR (dB) | GFlops | Inference Time (ms) |
|-----------------|-----------|--------|---------------------|
| PCNet           | 30.0      |        | 33.38               |
| Restormer       | 30.5      | 125    | 568                 |
| ELF (Ours)      | 30.9      | 66.39  | 33.38               |
| ELF-LW (Ours)   | 31.4      | 21.53  | 40.23               |
| PreNet          | 31.5      | 568    | 125                 |
| IADN            | 32.0      | 568    | 125                 |
| MSPFN           | 32.3      |        | 33.38               |
| MPRNet          | 32.5      | 66.39  | 33.38               |
| SWAL            | 32.9      | 512    | 33.38               |
| Restormer       | 33.2      |        | 33.38               |
| PCNet           | 33.4      | 512    | 33.38               |

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Figure 3: The architecture of our proposed ELF deraining method. It consists of an image deraining network (IDN), a multi-input attention module (MAM), and a background reconstruction network (BRN). IDN learns the corresponding rain distribution $I_{\text{rain},S}^*$ from the sub-sample $I_{\text{rain},S}$, and produces the corresponding deraining result $I_{\text{rain}}^*$ by subtracting $I_{\text{rain},S}^*$. Then, MAM takes $I_{\text{rain},S}$, $I_{\text{rain}}^*$, and $I_{B,S}^*$ as inputs, where the predicted rain distribution provides the prior (local and degree) to exploit complementary background components $f_{\text{IR}}$ from $I_{\text{rain}}$ to promote the background recovery.

2.1 Single Image Deraining

Traditional deraining methods [23, 23, 36] adopt image processing techniques and hand-crafted priors to address the rain removal problem. However, these methods produce unsatisfactory results when the predefined model do not hold. Recently, deep-learning based approaches [19, 27, 61] have emerged for rain streak removal and demonstrated impressive restoration performance. Early deep learning-based deraining approaches [9, 10] apply convolution neural networks (CNNs) to directly reduce the mapping range from input to output and produce rain-free results. To better represent the rain distribution, researchers take rain characteristics such as rain density [62], size and the veiling effect [27, 29] into account, and use recurrent neural networks to remove rain streaks via multiple stages [31] or the non-local network [45] to exploit long-range spatial dependencies for better rain streak removal [26]. Further, self-attention (SA) is recently introduced to eliminate the rain degradation with its powerful global correlation learning, and achieves impressive performance. Although the token compressed representation and global non-overlapping window-based SA [16, 51] are adopted to promote the global SA to alleviate the computational burden, these models still quickly overtax the computing resource. Apart from the low efficiency, these methods [16, 58] regard the deraining task as the rain perturbation removal only, ignoring the additional degradation effects of missing details and contrast bias.

2.2 Vision Transformers

Transformer-based models are first developed for sequence processing in natural language tasks [43]. Due to the distinguishing feature of the strong capability to learn long-range dependencies, ViT [8] introduces Transformer into computer vision field, and then a plenty of Transformer-based methods have been applied to vision tasks such as image recognition [8, 15], segmentation [48], object detection [3, 35]. Vision Transformers [8, 42] decompose an image into a sequence of patches (local windows) and learn their mutual relationships, which is adaptable to the given input content [24]. Especially for low-level vision tasks, since the global feature representation promotes accurate texture inference, Transformer models have been employed to solve the low-level vision problems [32, 51]. For example, TTSR [53] proposes a self-attention module to transfer the texture information in the reference image to the high-resolution image reconstruction, which can deliver accurate texture features. Chen et al. [4] propose a pre-trained image processing transformer on the ImageNet datasets and uses the multi-head architecture to process different tasks separately. However, the direct application of SA fails to exploit the full potential of Transformer, resulting from heavy self-attention computation load and inefficient communications across different depth (scales) of layers. Moreover, little effort has been made to consider the intrinsic complementary characteristics between Transformer and CNNs to construct a compact and practical model. Naturally, this design choice restricts the context aggregation within local neighborhoods, defying the primary motivation of using self-attention over convolutions, thus not ideally suited for image-restoration tasks. In contrast, we propose to explore the bridge, and construct a hybrid model of Transformer and CNN for image deraining task.

3 PROPOSED METHOD

Our main goal is to construct a high-efficiency and high-accuracy deraining model by taking advantage of the CNN and Transformer. Theoretically, the self-attention (SA) averages feature map values with the positive importance-weights to learn the global representation while CNNs tend to aggregate the local correlated information. Intuitively, it is reasonable to combine them to fully exploit the local and global textures. A few studies try to combine these two structures to form a hybrid framework for low-level image restoration but have failed to give full play to it. Taking the image deraining as an example, unlike the existing Transformer-based methods that directly apply Transformer blocks to replace convolutions, we consider the high efficiency and compatibility of these two structures, and construct a hybrid framework, dubbed ELF to harmonize their advantages for image deraining. Compared to the existing deraining methods, our proposed ELF departs from them in at least two key aspects. Differences in design concepts: unlike the additive composite model that predicts the optimal approximation $I_{B}^*$ of background
Thus, the function of IDN. Sampled rainy image \( I \) is first input to IDN to generate the corresponding sub-samples (\( I_{\text{BRN},3} \)) with the similar statistical distribution to the original one, shown in Figure 3. The efficiency, IDN and BRN share the same dual-path hybrid fusion module (MAM), and a background recovery network (BRN). For observing that the reconstructed rainy image \( \hat{I}_{\text{Rain}} \) has the similar statistical distribution to the original one, shown in Figure 3, the backbone of ELF contains a dual-path hybrid fusion network, involving one residual Transformer branch (RTB) and one encoder-decoder branch (EDB) to characterize global structure (low-frequency components) and local textures (high-frequency components), respectively.

Figure 3 outlines the framework of our proposed ELF, which contains an image deraining network (IDN), a multi-input attention module (MAM), and a background recovery network (BRN). For efficiency, IDN and BRN share the same dual-path hybrid fusion network, which are elaborated in Section 3.2.

### 3.1 Pipeline and Model Optimization

Given a rainy image \( I_{\text{Rain}} \in \mathbb{R}^{H \times W \times 3} \) and its clean version \( I_{\text{B}} \in \mathbb{R}^{H \times W \times 3} \), where \( H \) and \( W \) denote the spatial height and weight, we observe that the reconstructed rainy image \( \hat{I}_{\text{Rain},3} \in \mathbb{R}^{H \times W \times 3} \) via bilinear interpolation from the sampled rainy image \( I_{\text{Rain},3} \in \mathbb{R} \) has the similar statistical distribution to the original one, shown in Figure 4. This inspires us to predict the rain streak distribution at sampling space to alleviate the learning and computational burden.

In this way, we first sample \( I_{\text{Rain}} \) and \( I_{\text{B}} \) with Bilinear operation to generate the corresponding sub-samples (\( I_{\text{Rain},3} \in \mathbb{R} \) and \( I_{\text{BRN},3} \in \mathbb{R} \)). As illustrated before, our ELF contains two subnetworks (IDN and BRN) to complete the image deraining via association learning. Thus, \( I_{\text{Rain},3} \) is then input to IDN to generate the corresponding rain distribution \( I_{R,3} \) and deraining result \( I_{\text{BS},3} \), expressed as

\[
I_{R,3} = G_{\text{IDN}}(F_{\text{BS}}(I_{\text{Rain},3})),
\]

where \( F_{\text{BS}}(\cdot) \) denotes the Bilinear downsampling to generate the sampled rainy image \( I_{\text{Rain},3} \). \( G_{\text{IDN}}(\cdot) \) refers to the rain estimation function of IDN.

Rain distribution reveals the degradation location and degree, which is naturally reasonable to be translated into the degradation prior to help accurate background recovery. Before passing \( I_{\text{BS},3} \) into BRN for background reconstruction, a multi-input attention module (MAM), shown in Figure 3, is designed to fully exploit the complementary background information from the rainy image \( I_{\text{Rain}} \) via the Transformer layer, and merge them to the embedding representation of \( I_{\text{BS},3} \). These procedures of MAM are expressed as

\[
\begin{align*}
    f_{\text{BT}} &= F_{\text{SA}}(I_{\text{BS},3}, I_{\text{Rain}}), \\
    f_{\text{MAM}} &= F_{\text{HFB}}(f_{\text{BT}}, F_{\text{BS}}(I_{\text{BS},3})).
\end{align*}
\]

In Equation (2), \( F_{\text{SA}}(\cdot) \) denotes self-attention functions, involving the embedding function and dot-product interaction. \( F_{\text{BT}}(\cdot) \) is the embedding function to generate the initial representation of \( I_{\text{BS},3} \). \( F_{\text{HFB}}(\cdot) \) refers to the fusion function in HFB. Following that, BRN takes \( f_{\text{MAM}} \) as input for background reconstruction as

\[
I_{\text{BS}} = G_{\text{BRN}}(f_{\text{MAM}}) + F_{\text{UP}}(I_{\text{BS},3}),
\]

where \( G_{\text{BRN}}(\cdot) \) denotes the super-resolving function of BRN, and \( F_{\text{UP}}(\cdot) \) is the Bilinear upsampling.

Unlike the individual training of rain streak removal and background recovery, we introduce the joint constraint to enhance the compatibility of the deraining model with background recovery, automatically learned from the training data. Then the image loss (Charbonnier penalty loss \([13, 22, 25]\)) and structural similarity (SSIM) \([50]\) loss are employed to supervise networks to achieve the image and structural fidelity restoration simultaneously. The loss functions are given by

\[
\begin{align*}
    \mathcal{L}_{\text{IDN}} &= \sqrt{(I_{R,3} - I_{\text{BS}})^2 + \epsilon^2} + \alpha \times \text{SSIM}(I_{R,3}, I_{\text{BS}}), \\
    \mathcal{L}_{\text{BRN}} &= \sqrt{(I_{\text{BS}} - I_{\text{B}})^2 + \epsilon^2} + \alpha \times \text{SSIM}(I_{\text{BS}}, I_{\text{B}}), \\
    \mathcal{L} &= \mathcal{L}_{\text{IDN}} + \lambda \times \mathcal{L}_{\text{BRN}},
\end{align*}
\]

where \( \alpha \) and \( \lambda \) are used to balance the loss components, and experimentally set as \(-0.15\) and \(1\), respectively. The penalty coefficient \( \epsilon \) is set to \(10^{-3}\).

### 3.2 Hybrid Fusion Network

It is known that the self-attention mechanism is the core part of Transformer, which is good at learning long-range semantic dependencies and capturing global structure representation in the image. Conversely, CNNSs are skilled at modeling the local relations due to the intrinsic local connectivity. To this end, we construct the backbone of IDN and BRN into a deep dual-path hybrid fusion network by unifying the advantages of Transformer and CNNSs. As shown in Figure 3, the backbone involves a residual Transformer branch (RTB) and an encoder-decoder branch (EDB). RTB takes a few learnable tokens (feature channels) as input and stacks multi-head attention and feed-forward networks to encode the global structure. However, capturing long-range pixel interactions is the culprit for the enormous amount of Transformer computational, making it infeasible to apply to high-resolution images, especially for the image restoration task. Besides processing the feature representation on the sampled space, inspired by [1], instead of learning the global spatial similarity, we apply SA to compute cross-covariance...
we use Bilinear sampling followed by a Transformer to fully exploit the complementary background information for enhancement. Unlike the standard Transformer receiving a sequence of image patches as input, MAM takes the predicted rain distribution \( f_{RS} \) and rainy image \( I_{Rain} \) as inputs, and first learns the embedding representation \( f_{B,S} \), enriched with local contexts. \( f_{RS} \) and \( f_{Rain} \) serve as query (Q), key (K) and value (V) projections. Instead of learning the spatial attention map of size \( \mathbb{R}^{HW \times HW} \), we then reshape query and key projections, and generate cross-covariance transposed-attention map \( M \in \mathbb{R}^{C \times C} \) via the dot-product interaction between \( f_{RS} \) and \( f_{Rain} \). As shown in Figure 5, the attention map guides the network to excise background texture information \( f_{BT} \) from the embedding representation \( f_{Rain} \) of \( I_{Rain} \). The procedures in SA are expressed as

\[
F_{SA} = \text{Softmax} (F_k (I_{RS}) \circ F_Q (I_{Rain}))) \circ F_V (I_{Rain})
\]

where \( F_k (\cdot), F_Q (\cdot) \) and \( F_V (\cdot) \) are the embedding functions to produce the projections. \( \circ \) denotes the dot-product interaction and softmax function. Followed by a hybrid fusion block, the extracted complementary information is merged with the embedding representation of \( I_{RS} \) to enrich background representation.

### 3.3 Multi-input Attention Module

To associate rain streaks removal and background recovery, as shown in Figure 3, we construct a multi-input attention module (MAM) with Transformer to fully exploit the complementary background information for enhancement. Unlike the standard Transformer receiving a sequence of image patches as inputs, MAM takes the predicted rain distribution \( f_{RS} \), sub-space deraining image \( I_{B,S} \) and rainy image \( I_{Rain} \) as inputs, and first learns the embedding representation \( f_{B,S}, f_{RS}, f_{Rain} \), enriched with local contexts. \( f_{RS} \) and \( f_{Rain} \) serve as query (Q), key (K) and value (V) projections. Instead across channels to generate the attention map encoding global contexts implicitly. It has linear complexity rather than quadratically complexity.

EDB is designed to infer locally-enriched textures. Inspired by U-Net [41], we also construct EDB with the U-shaped framework. The first three stages form the encoder, and the remaining three stages represent the decoder. Each stage takes a similar architecture, consisting of sampling layers, residual channel attention blocks (RCABs) [64] and hybrid fusion block. Instead of using the strided or transposed convolution for rescaling spatial resolution of features, we use Bilinear sampling followed by a 1 × 1 convolution layer to reduce checkerboard artifacts and model parameters. To facilitate residual feature fusion at different stages or scales, we design HFB to aggregate multiple inputs among stages in terms of the spatial and channel dimensions. HFB enables more diverse features to be fully used during the restoration process.

Moreover, to further reduce the number of parameters, RTB and EDB are equipped with depth-wise separable convolutions (DSC). For RTB, we integrate DSC into multi-head attention to emphasize on the local context before computing feature covariance to produce the global attention map. Moreover, we construct EDB into an asymmetric U-shaped structure, in which the encoder has the portable design with DSC, but the standard convolutions for the decoder. This scheme can save about 8% parameters of the whole network. We have experimentally verified that utilizing DSC in the encoder is better than that in the decoder.

### 4 Experiments

To validate our proposed ELF, we conduct extensive experiments on synthetic and real-world rainy datasets, and compare ELF with several mainstream image deraining methods. These methods include MPRNet [59], SWAL [14], RCDNet [46], DDRNet [7], MSPFN [18], IADN [17], PreNet [40], UMRL [56], DIDMDN [62], RESCAN [31] and DDC [30]. Five commonly used evaluation metrics, such as Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), Feature

| Model | SA | SR | DSC | HFB | MAM | SSIM | PSNR | SSIM | Par. | Time | GFlops |
|-------|----|----|-----|-----|-----|------|------|------|-----|------|--------|
| Rain Image | – | – | – | – | – | 22.16 | 0.732 | – | – | – | – |
| w/o SA | ✓ | ✓ | ✓ | ✓ | ✓ | 32.78 | 0.919 | 1.536 | 50.24 | 50.24 |
| w/o DSC | ✓ | ✓ | ✓ | ✓ | ✓ | 32.73 | 0.918 | 1.518 | 0.121 | 62.37 |
| w/o HFB | ✓ | ✓ | ✓ | ✓ | ✓ | 32.56 | 0.917 | 1.539 | 0.102 | 69.41 |
| w/o MAM | ✓ | ✓ | ✓ | ✓ | ✓ | 31.46 | 0.906 | 1.516 | 0.121 | 64.28 |
| w/o SSIM | ✓ | ✓ | ✓ | ✓ | ✓ | 33.17 | 0.919 | 1.532 | 0.125 | 66.39 |
| w/o all | ✗ | ✗ | ✗ | ✗ | ✗ | 29.05 | 0.861 | 1.538 | 0.046 | 61.24 |
| ELF | ✗ | ✗ | ✗ | ✗ | ✗ | 32.97 | 0.921 | 1.519 | 0.156 | 214.67 |
| ELF ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 33.38 | 0.925 | 1.532 | 0.125 | 66.39 |

Table 1: Ablation study on the depth-wise separable convolutions (DSC), multi-input attention module (MAM), hybrid fusion block (HFB), SSIM loss, super-resolution (SR), residual Transformer branch (RTB) and encoder-decoder branch (EDB) on Test1200 dataset. We obtain the model parameters (Million (M)), average inference time (Second (S)), and calculation complexity (GFlops (G)) of deraining on images with the size of 512 × 512.
4.1 Implementation Details

**Data Collection.** Since there exits the discrepancy in training samples for all comparison methods, following [17, 18], we use 13,700 clean/rain image pairs from [10, 63] for training all comparison methods with their publicly released codes by tuning the optimal settings for a fair comparison. For testing, four synthetic benchmarks (Test100 [63], Test1200 [62], R100H and R100L [54]) and three real-world datasets (Rain in Driving (RID), Rain in Surveillance (RIS) [28] and Real127 [62]) are considered for evaluation.

**Experimental Setup.** In our baseline, the number of Transformer blocks in RTB is set to 10 while RCAB is empirically set to 1 for each stage in EDB with filter numbers of 48. The training images are coarsely cropped into small patches with a fixed size of 256 × 256 pixels to obtain the training samples. We use Adam optimizer with the learning rate (2 × 10^{−4} with the decay rate of 0.8 at every 65 epochs till 600 epochs) and batch size (12) to train our ELF on a single Titan Xp GPU.

4.2 Ablation Study

**Validation on Basic Components.** We conduct ablation studies to validate the contributions of individual components, including the self-attention (SA), depth-wise separable convolutions (DSC), super-resolution reconstruction (SR), hybrid fusion block (HFB) and multi-input attention module (MAM) to the final deraining performance. For simplicity, we denote our final model as ELF and devise the baseline model w/o all by removing all these components above. Quantitative results in terms of deraining performance and inference efficiency on the Test1200 dataset are presented in Table 1, revealing that the complete deraining model ELF achieves significant improvements over its incomplete versions. Compared to w/o MAM model (removing MAM from ELF), ELF achieves 1.92dB performance gain since the association learning in MAM can help the network to fully exploit the background information from the rainy input with the predicted rain distribution prior. In addition, disentangling the image deraining task into rain streaks removal and texture reconstruction at the low-dimension space exhibits considerable superiority in terms of efficiency (19.8% and 67.6% more efficient in inference time and computational cost, respectively) and restoration quality (referring to the results of ELF and w/o RTB models). Moreover, EDB allows the network to aggregate multi-scale textural features, which is crucial to enrich the representation of local textures.

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**Validation on Basic Components.** We conduct ablation studies to validate the contributions of individual components, including the self-attention (SA), depth-wise separable convolutions (DSC), super-resolution reconstruction (SR), hybrid fusion block (HFB) and multi-input attention module (MAM) to the final deraining performance. For simplicity, we denote our final model as ELF and devise the baseline model w/o all by removing all these components above. Quantitative results in terms of deraining performance and inference efficiency on the Test1200 dataset are presented in Table 1, revealing that the complete deraining model ELF achieves significant improvements over its incomplete versions. Compared to w/o MAM model (removing MAM from ELF), ELF achieves 1.92dB performance gain since the association learning in MAM can help the network to fully exploit the background information from the rainy input with the predicted rain distribution prior. In addition, disentangling the image deraining task into rain streaks removal and texture reconstruction at the low-dimension space exhibits considerable superiority in terms of efficiency (19.8% and 67.6% more efficient in inference time and computational cost, respectively) and restoration quality (referring to the results of ELF and w/o RTB models). Moreover, EDB allows the network to aggregate multi-scale textural features, which is crucial to enrich the representation of local textures.

4.3 Comparison with State-of-the-arts

**Synthesized Data.** Quantitative results on Test1200, Test100, 100H and R100L datasets are provided in Table 2. Meanwhile, the inference time, model parameters and computational cost are also compared. It is observed that most of the deraining models obtain impressive performance on light rain cases with high consistency. However, only our ELF and MPRNet still perform favorably on heavy rain conditions, exhibiting great superiority over other competing methods in terms of PSNR. As expected, our ELF model achieves the best scores on all metrics, surpassing the CNN-based SOTA (MPRNet) by 0.25 dB on average, but only accounts for its 11.7% and 42.1% computational cost and parameters. Meanwhile, our light-weight deraining model ELF-LW is still competitive, which gains the third-best average PSNR score on four datasets. In particular, ELF-LW averagely surpasses the real-time image deraining method PCNet [21] by 1.08dB, while with less parameters (saving 13.6%) and computational cost (saving 23.7%).

For more convincing evidence, we also provide visual comparisons in Figure 6. High-accuracy methods, such as PreNet, MSFFN and RCDNet, can effectively eliminate the rain layer and thus bring an improvement in visibility. But they fail to generate visual appealing results by introducing considerable artifacts and unnatural color appearance, the heavy rain condition in particular. Likewise, DRDNet focuses on the detail recovery, but shows undesired deraining performance. MPRNet tends to produce over-smoothing results. Besides recovering cleaner and more credible image textures, our ELF produces results with better contrast and less color distortion. Please refer to the “tiger” and “horse” scenarios. Moreover, We speculate that these visible improvements on restoration quality may benefit from our proposed hybrid representation framework of Transformer and CNN as well as the association learning scheme for rain streak removal and background recovery. These strategies are integrated into a unified framework, allowing the network to fully exploit the respective learning merits for image deraining while guaranteeing the inference efficiency.

**Real-world Data.** We further conduct experiments on three real-world datasets: Real127 [62], Rain in Driving (RID), and Rain in Surveillance (RIS) [28]. Quantitative results of NIQE [37] and SSEQ [34] are listed in Table 3, where smaller NIQE and SSEQ scores indicate better perceptual quality and clearer contents. Again, our proposed ELF is highly competitive, achieving the lowest average values on the RID and RIS datasets. We visualize the deraining results in Figure 7, showing that ELF produces rain-free images with cleaner and more credible contents, whereas the competing models fail to remove rain streaks. These evidences indicate that our ELF model performs well in eliminating rain perturbation while preserving textural details and image naturalness.
Table 2: Comparison results of average PSNR, SSIM, and FSIM on Test100/Test1200/R100H/R100L datasets. When averaged across all four datasets, our ELF advances state-of-the-art (MPRNet) by 0.25 dB, but accounts for only its 11.7% and 42.1% corresponding rain-free outputs. We then apply the publicly available procedures are directly applied to the rainy images to generate corresponding deraining methods, the restoration processes while preserving credible textural details is crucial for object detection. This motivates us to investigate the effect of deraining methods. Visual comparisons on two instances in Figure 8 indicate that ELF achieves highest PSNR scores on COCO350 and BDD350 pre-trained models of YOLOv3 for the detection task. Table 4 shows that ELF facilitates better object detection performance than other deraining methods. Visual comparisons on two instances in Figure 8 indicate that the deraining images by ELF exhibit a notable superiority in terms of image quality and detection accuracy. We attribute the considerable performance improvements of both deraining and down-stream detection tasks to our association learning between rain streaks removal and detail recovery tasks.

4.4 Impact on Downstream Vision Tasks
Eliminating the degraded effects of rain streaks under rainy conditions while preserving credible textural details is crucial for object detection. We then apply the publicly available pre-trained models of YOLOv3 for the detection task. Table 4 shows that ELF achieves highest PSNR scores on COCO350 and BDD350 datasets [18]. Meanwhile, the rain-free results generated by ELF facilitate better object detection performance than other deraining methods. Visual comparisons on two instances in Figure 8 indicate that the deraining images by ELF exhibit a notable superiority in terms of image quality and detection accuracy. We attribute the considerable performance improvements of both deraining and down-stream detection tasks to our association learning between rain streaks removal and detail recovery tasks.

Figure 6: Visual comparison of derained images obtained by seven methods on R100H/R100L/Test100/Test1200 datasets. Please refer to the region highlighted in the boxes for a close up comparison.

Table 3: Comparison of average NIQE/SSEQ scores with ten deraining methods on three real-world datasets.

| Datasets       | DIDMDN | RESCAN* [31] | DDC [30] | LPNet [11] | UMRL [56] | PreNet* [40] | IADN [17] | MSPFN [18] | DRDNet [7] | RCDNet [46] | MPRNet [59] | SWAL [14] | ELF (Ours) | ELF (Ours) |
|---------------|--------|--------------|----------|------------|-----------|--------------|----------|------------|------------|-------------|------------|------------|------------|------------|
| Real127 (127) | 3.926/32.42 | 3.852/30.09  | 4.022/29.33 | 3.989/29.62 | 3.984/29.48 | 3.835/29.61  | 3.769/29.12 | 3.816/29.05 | 4.208/30.34 | 3.965/30.05 | 3.735/29.16 |
| RID (2495)    | 5.693/41.71  | 5.641/40.62  | 6.247/40.25 | 6.783/42.06 | 6.757/41.04 | 7.007/43.04  | 6.035/40.72 | 6.518/40.47 | 5.715/39.98 | 6.452/40.16 | 4.318/37.89 |
| RIS (2348)    | 5.751/46.36  | 6.485/50.89  | 5.826/47.80 | 6.396/53.09 | 5.615/43.45 | 6.722/48.22  | 5.909/42.95 | 6.135/43.47 | 6.269/45.34 | 6.610/48.78 | 5.835/42.16 |

Table 4: Comparison of average NIQE/SSEQ scores with ten deraining methods on three real-world datasets.
Figure 7: Visual comparison of derained images obtained by eight methods on five real-world scenarios, covering rain veiling effect (1st), heavy rain (2nd) and light rain (3rd-4th). Please refer to the region highlighted in the boxes for a close up comparison.

Figure 8: Visual comparison of joint image deraining and object detection on BDD350 dataset.

Table 4: Comparison results of joint image deraining and object detection on COCO350/BDD350 datasets.

| Methods        | Rain input | RESCAN [31] | PreNet [40] | IADN [17] | MSPFN [18] | MPRNet [59] | ELF-LW   | ELF (Ours) |
|----------------|------------|-------------|-------------|------------|-------------|-------------|----------|------------|
| Deraining:     | COCO350/BDD350; Image Size: 640×480/1280×720 |
| PSNR           | 14.79/14.13 | 17.04/16.71 | 17.53/16.90 | 18.18/17.91 | 18.23/17.85 | 17.99/16.83 | 18.43/18.09 | 18.93/18.49 |
| SSIM           | 0.648/0.470 | 0.745/0.646 | 0.765/0.652 | 0.790/0.719 | 0.782/0.761 | 0.769/0.622 | 0.800/0.714 | 0.818/0.761 |
| Ave.inf.time (s) | --/--     | 0.546/1.532 | 0.227/0.764 | 0.135/0.412 | 0.584/1.246 | 0.181/0.296 | 0.076/0.160 | 0.128/0.263 |
| Object Detection; Algorithm: YOLOv3; Dataset: COCO350/BDD350; Threshold: 0.6 |
| Precision (%)  | 23.03/36.86 | 28.74/40.33 | 31.31/38.66 | 32.92/40.28 | 32.56/41.04 | 31.31/40.49 | 33.31/40.88 | 33.85/41.84 |
| Recall (%)     | 29.60/42.80 | 35.61/47.79 | 37.92/48.59 | 39.83/50.25 | 39.31/50.40 | 38.98/48.77 | 40.43/51.55 | 40.43/52.60 |
| IoU (%)        | 55.50/39.85 | 59.81/61.98 | 60.75/61.08 | 61.96/62.27 | 61.69/62.42 | 61.14/61.99 | 62.21/62.48 | 62.61/62.80 |

5 CONCLUSION

We rethink the image deraining as a composite task of rain streak removal, textures recovery and their association learning, and propose a dynamic associated network (ELF) for image deraining. Accordingly, a two-stage architecture and an associated learning module (ALM) are adopted in ELF to account for twin goals of rain streak removal and texture reconstruction while facilitating the learning capability. Meanwhile, the joint optimization promotes the compatibility while maintaining the model compactness. Extensive results on image deraining and joint detection task demonstrate the superiority of our ELF model over the state-of-the-arts.

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