Towards Ground Truth for Single Image Deraining

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Abstract. We propose a large-scale dataset of real-world rainy and clean image pairs and a method to remove degradations, induced by rain streaks and rain accumulation, from the image. As there exists no real-world dataset for deraining, current state-of-the-art methods rely on synthetic data and thus are limited by the sim2real domain gap; moreover, rigorous evaluation remains a challenge due to the absence of a real paired dataset. We fill this gap by collecting the first real paired deraining dataset through meticulous control of non-rain variations. Our dataset enables paired training and quantitative evaluation for diverse real-world rain phenomena (e.g. rain streaks and rain accumulation). To learn a representation invariant to rain phenomena, we propose a deep neural network that reconstructs the underlying scene by minimizing a rain-invariant loss between rainy and clean images. Extensive experiments demonstrate that the proposed dataset benefits existing derainers, and our model can outperform the state-of-the-art deraining methods on real rainy images under various conditions.

Keywords: Single-image rain removal, Real deraining dataset

1 Introduction

Single-image deraining aims to remove degradations induced by rain from images. Restoring rainy images can not only improve their aesthetic properties, but also supports reuse of abundant publicly available pretrained models across computer vision tasks. Top performing methods use deep networks, but suffer from a common issue: it is not possible to obtain ideal real ground-truth pairs of rain and clean images. The same scene, in the same space and time, cannot be observed both with and without rain. To overcome this, deep learning based rain removal relies on synthetic data.

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The use of synthetic data for deraining is very prevalent. However, current rain simulators cannot model all the complex effects of rain, which leads to unwanted artifacts when applying models trained on them to real-world rainy scenes. For instance, a number of synthetic methods add rain streaks to clean images to generate the pair, but rain does not only manifest as streaks: If raindrops are further away, the streaks meld together, creating rain accumulation, or veiling effects, which are exceedingly difficult to simulate. A further challenge with synthetic data is that results on real test data can only be evaluated qualitatively, for no real paired ground truth exists.

Realizing these limitations of synthetic data, we tackle the problem from another angle by relaxing the concept of ideal ground truth to a sufficiently short time window (see Fig. 1). We decide to conduct the experiment of obtaining short time interval paired data, particularly in light of the timely growth and diversity of landscape YouTube live streams. We strictly filter such videos with objective criteria on illumination shifts, camera motion, and motion artifacts. Further correction algorithms are applied for subtle variations, such as slight movements of foliage. We call this dataset GT-RAIN, as it is a first attempt to provide real paired ground truth for deraining. Although our dataset relies on streamers, YouTube’s fair use policy allows its release to the academic community. Please refer to Fig. 1 for an illustration of a comparison between GT-RAIN and other existing datasets.

Defining “real, paired ground truth”: Clearly, obtaining real, paired ground truth data by capturing a rain and rain-free image pair at the exact same space...
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and time is not feasible. However, the dehazing community has accepted several test sets following these guidelines as a satisfactory replacement for evaluation purposes:

- A pair of degraded and clean images is captured as real photos at two different timestamps;
- Illumination shifts are limited by capturing data on cloudy days;
- The camera configuration remains identical while capturing the degraded and clean images.

We produce the static pairs in GT-RAIN by following the above criterion set forth by the dehazing community while enforcing a stricter set of rules on sky and local motion. More importantly, as a further step closer towards obtaining real ground truth pairs, we capture natural weather effects instead, which address problems of scale and variability that inherently come with simulating weather through man-made methods. We demonstrate that on average, methods trained on our proposed dataset improve in performance by 1dB. Additionally, in the results of the proposed method, we not only see quantitative and qualitative improvements, but also showcase a unique ability to handle diverse rain physics that could not previously be handled through synthetic methods.

1.1 Contributions

In summary, we make the following contributions:

- We propose a real-world paired dataset: GT-RAIN. The dataset captures real rain phenomena, from rain streaks to accumulation under various rain fall conditions, to bridge the domain gap that is too complex to be modeled by synthetic and semi-real datasets.
- We introduce an avenue for the deraining community to now have standardized quantitative and qualitative evaluations. Previous evaluations were quantifiable only wrt. simulations.
- We propose a framework to reconstruct the underlying scene by learning representations invariant to the rain phenomena via a rain-invariant loss function. Our approach outperforms the state of the art by 12.3% PSNR on average for deraining real images.

2 Related Work

Rain physics: Raindrops exhibit diverse physical properties while falling, and many experimental studies have been conducted to investigate these, including the equilibrium shape, size, terminal velocity, spatial distribution, and temporal distribution. A mixture of these distinct properties transforms the photometry of a raindrop into a complex mapping of the environmental radiance which considers refraction, specular reflection, and internal reflection:

\[
L(\hat{n}) = L_r(\hat{n}) + L_s(\hat{n}) + L_p(\hat{n}),
\]  

(1)
Table 1. Our proposed large-scale dataset enables paired training and quantitative evaluation for real-world deraining. We consider SPA-Data [46] as a semi-real dataset since it only contains real rainy images, where the pseudo ground-truth images are synthesized from a rain streak removal algorithm.

| Dataset         | Type      | Rain Effects                              | Size  |
|-----------------|-----------|-------------------------------------------|-------|
| Rain12 [30]     | Simulated | Synth. streaks only                       | 12    |
| Rain100L [52]   | Simulated | Synth. streaks only                       | 300   |
| Rain800 [57]    | Simulated | Synth. streaks only                       | 800   |
| Rain100H [52]   | Simulated | Synth. streaks only                       | 1.9K  |
| Outdoor-Rain [28] | Simulated | Synth. streaks & Synth. accumulation      | 10.5K |
| RainCityscapes [18] | Simulated | Synth. streaks & Synth. accumulation      | 10.62K |
| Rain12000 [56]  | Simulated | Synth. streaks only                       | 13.2K |
| Rain14000 [12]  | Simulated | Synth. streaks only                       | 14K   |
| NYU-Rain [28]   | Simulated | Synth. streaks & Synth. accumulation      | 16.2K |
| SPA-Data [46]   | Semi-real | Real streaks only                         | 29.5K |
| Proposed        | Real      | Real streaks & Real accumulation          | 31.5K |

where \( L(\hat{n}) \) is the radiance at a point on the raindrop surface with normal \( \hat{n} \), \( L_r(\cdot) \) is the radiance of the refracted ray, \( L_s(\cdot) \) is the radiance of the specularly reflected ray, and \( L_p(\cdot) \) is the radiance of the internally reflected ray. In real images, the appearance of rain streaks is also affected by motion blur and background intensities. Moreover, the dense rain accumulation results in sophisticated veiling effects. Interactions of these complicated phenomena make it challenging to simulate realistic rain effects on real images. Until GT-RAIN, previous works [46,22,45,55,15,28,19] have relied heavily on simulated rain and are limited by the sim2real gap.

**Deraining datasets:** Most data-driven deraining models require paired rainy and clean, rain-free ground-truth images for training. Due to the difficulty of collecting real paired samples, previous works focus on synthetic datasets, such as Rain12 [30], Rain100L [52], Rain100H [52], Rain800 [57], Rain12000 [56], Rain14000 [12], NYU-Rain [28], Outdoor-Rain [28], and RainCityscapes [18]. Even though synthetic images from these datasets incorporate some physical characteristics of real rain, significant gaps still exist between synthetic and real data [53]. More recently, a “paired” dataset with real rainy images (SPA-Data) was proposed in [46]. However, their “ground-truth” images are in fact a product of a video-based deraining method – synthesized based on the temporal motions of raindrops which may introduce artifacts and blurriness; moreover, the associated rain accumulation and veiling effects are not considered. In contrast, we collect pairs of real-world rainy and clean ground-truth images by enforcing rig-
Fig. 2. We collect the first real paired deraining dataset by rigorously controlling the environmental variations. First, we remove heavily degraded videos such as scenes without proper exposure, noise, or water droplets on the lens. Next, we carefully choose the rainy and clean frames as close as possible in time to mitigate illumination shifts before cropping to remove large movement. Lastly, we correct for small camera motion (due to strong wind) using SIFT [32] and RANSAC [9] and perform elastic image registration [43,44] by estimating the displacement field when necessary.

3 Dataset

We now describe our method to control variations in a real dataset of paired images taken at two different timestamps, as illustrated in Fig. 2.

Data collection: We collect rain and clean ground-truth videos using a Python program based on FFmpeg to download videos from YouTube live streams across
Fig. 3. Our proposed dataset contains diverse rainy images collected across the world. We illustrate several representative image pairs with various rain streak appearances and rain accumulation strengths at different geographic locations.

Collection criteria: To minimize variations between rainy and clean frames, videos are filtered based on a strict set of collection criteria. Note that we perform realignment for camera and local motion only when necessary – with manual oversight to filter out cases where motion still exists after realignment. Please see examples of motion correction and alignment in the supplement.

- **Heavily degraded scenes** that contain excessive noise, webcam artifacts, poor resolution, or poor camera exposure are filtered out as the underlying scene cannot be inferred from the images.
- **Water droplets** on the surface of the lens occlude large portions of the scene and also distort the image. Images containing this type of degradation are filtered out as it is out of the scope of this work – we focus on rain streak and rain accumulation phenomena.
- **Illumination shifts** are mitigated by minimizing the time difference between rainy and clean frames. Our dataset has an average time difference of 25 minutes, which drastically limits large changes in global illumination due to sun position, clouds, etc.
- **Background changes** containing large discrepancies (e.g., cars, people, swaying foliage, water surfaces) are cropped from the frame to ensure that clean and rainy images are aligned. By limiting the average time difference between scenes, we also minimize these discrepancies before filtering. All sky regions are cropped out as well to ensure proper background texture.
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– **Camera motion.** Adverse weather conditions, such as heavy wind, can cause camera movements between the rainy and clean frames. To address this, we use the Scale Invariant Feature Transform (SIFT) [32] and Random Sample Consensus (RANSAC) [9] to compute the homography matrix to realign the frames.

– **Local motion.** Despite controlling for motion whenever possible, certain scenes still contain small local movements that are unavoidable, especially in areas of foliage. To correct for this, we perform elastic image registration when necessary by estimating the displacement field [43,44].

**Dataset statistics:** Our large-scale dataset includes a total of 31,524 rainy and clean frame pairs, which is split into 26,124 training frames, 3,300 validation frames, and 2,100 testing frames. These frames are taken from a total of 101 videos covering a large variety of background scenes from urban locations (e.g. buildings, streets, cityscapes) to natural scenery (e.g. forests, plains, hills). We cover a wide range of geographic locations from around the world (e.g. North America, Europe, Oceania, Asia) to ensure that we capture diverse scenes and rain fall conditions. The scenes also include varying degrees of illumination from different times of day. The webcams cover a wide array of resolutions, noise levels, intrinsic parameters (focal length, optical center, distortion), etc. We include rain of varying densities, streak lengths, shapes, and sizes. As a result, our dataset incorporates diverse rain effects that cannot be accurately reproduced by SPA-Data [46] or synthetic datasets [30,52,56,12,28,18]. Please refer to Fig. 3 for an illustration of several image pairs in GT-RAIN.

4 Learning to Derain Real Images

To handle greater diversity of rain streak appearance, we propose a method to learn a representation that is invariant to rain for real image deraining. Our framework is illustrated in Fig. 4.

4.1 Problem Formulation

Most existing derainers emphasize on the rain streak removal and rely on the following equation to model the real-world rain phenomenon [30,52,56,12,28,18]:

\[ I = J + \sum_{i=1}^{n} S_i, \]

where \( I \in \mathbb{R}^{3 \times H \times W} \) is the observed rainy image, \( J \in \mathbb{R}^{3 \times H \times W} \) is the rain-free or “clean” image, and \( S_i \) is the \( i \)-th rain layer. However, real-world rain can be more complicated due to the dense rain accumulation and the rain veiling effect [41,28,29]. These additional effects, which are visually similar to fog and mist, may cause severe image degradation, and thus removing them should
Fig. 4. By minimizing a rain-invariant objective, our model learns robust features for reconstruction. When training, a shared-weight encoder is used to extract features from rainy and ground-truth images. These features are then evaluated with the rain-invariant loss, where features from a rainy image and its ground-truth are encouraged to be similar. Learned features from the rainy images are also fed into a decoder to reconstruct the ground-truth images with MS-SSIM and ℓ1 loss functions.

also be a primary goal for single-image deraining. With GT-RAIN, it now becomes possible to study and conduct optically challenging, real-world rainy image restoration.

Given an image \( I \) of a scene captured during rain, we propose to learn a function \( F(\cdot, \theta) \) parameterized by \( \theta \) to remove degradation induced by the rain phenomena. This function is realized as a neural network (see Fig. 4) that takes as input a rainy image \( I \) and outputs a “clean” image \( \hat{J} = F(I, \theta) \in \mathbb{R}^{3 \times H \times W} \), where undesirable characteristics, i.e. rain streaks and rain accumulation, are removed from the image to reconstruct the underlying scene \( J \).

### 4.2 Rain-invariant Loss

To derain an image \( I \), one may directly learn a map from \( I \) to \( \hat{J} \) simply by minimizing the discrepancies between \( \hat{J} \) and the ground truth \( J \), i.e. an image reconstruction loss – such is the case for existing methods. Under this formulation, the model must explore an infinitely large hypothesis space, e.g. any region obfuscated by rain streaks is inherently ambiguous, making learning difficult.

Unlike previous works, we constrain the learned representation such that it is invariant to rain phenomena. To “learn away” the rain, we propose to map both the rainy and clean images of the same scene to an embedding space where they are close to each other by optimizing a similarity metric. Additionally, we minimize a reconstruction objective to ensure that the learned representation is sufficient to recover the underlying scene. Our approach is inspired by the recent advances in contrastive learning [6], and to the best of our knowledge, it is the first attempt to distill rain-invariant representations of real-world scenes by
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directly comparing the rainy and clean images in the feature space. But unlike [6], we do not define a positive pair as augmentation to the same image, but rather any rainy image and its corresponding clean image from the same scene.

When training, we first randomly sample a mini-batch of $N$ rainy images with the associated clean images to form an augmented batch $\{(I_i, J_i)\}_{i=1}^N$, where $I_i$ is the $i$-th rainy image, and $J_i$ is its corresponding ground-truth image. This augmented batch is fed into a shared-weight feature extractor $F_E(\cdot, \theta_E)$ with weights $\theta_E$ to obtain a feature set $\{(z_{I_i}, z_{J_i})\}_{i=1}^N$, where $z_{I_i} = F_E(I_i, \theta_E)$ and $z_{J_i} = F_E(J_i, \theta_E)$. We consider every $(z_{I_i}, z_{J_i})$ as the positive pairs. This is so that the learned features from the same scene should be close to each other regardless of the rainy conditions. We treat the other $2(N - 1)$ samples from the same batch as negative samples. Based on the noise-contrastive estimation (NCE) [16], we adopt the following InfoNCE [38] criterion to measure the rain-invariant loss for a positive pair $(z_{J_i}, z_{I_i})$:

$$\ell_{z_{J_i}, z_{I_i}} = -\log \frac{\exp \left(\frac{\cos(z_{I_i}, z_{J_i})}{\tau} \right)}{\sum_{k \in K} \exp \left(\frac{\cos(z_{J_i}, k)}{\tau} \right)},$$  \hspace{1cm} (3)

where $K = \{z_{J_j}, z_{I_j}\}_{j=1, j \neq i}^N$ is a set that contains the features extracted from other rainy and ground-truth images in the selected mini-batch, $\cos(u, v) = u^\top v / \|u\| \|v\|$ is the cosine similarity between two feature vectors $u$ and $v$, and $\tau$ is the temperature parameter [50]. We set $\tau$ as 0.25, and this loss is calculated across all positive pairs within the mini-batch for both $(z_{I_i}, z_{J_i})$ and $(z_{J_i}, z_{I_i})$.

### 4.3 Full Objective

While minimizing Eq. (3) maps features of clean and rainy images to the same subspace, we also need to ensure that the representation is sufficient to reconstruct the scene. Hence, we additionally minimize a Multi-Scale Structural Similarity Index (MS-SSIM) [48] loss and an $\ell_1$ image reconstruction loss to prevent the model from discarding useful information for the reconstruction task. Our full objective $L_{\text{full}}$ is as follows:

$$L_{\text{full}}(\hat{J}, J) = L_{\text{MS-SSIM}}(\hat{J}, J) + \lambda_{\ell_1} L_{\ell_1}(\hat{J}, J) + \lambda_{\text{invariant}} L_{\text{invariant}}(z_{J_i}, z_{I_i}),$$  \hspace{1cm} (4)

where $L_{\text{MS-SSIM}}(\cdot)$ is the MS-SSIM loss that is commonly used for image restoration [50]. $L_{\ell_1}(\cdot)$ is the $\ell_1$ distance between the estimated clean images $\hat{J}$ and the ground-truth clean images $J$. $L_{\text{invariant}}(\cdot)$ is the rain-invariant loss described in Sec. 4.2 and $\lambda_{\ell_1}$ and $\lambda_{\text{invariant}}$ are two hyperparameters to control the relative importance of different loss functions. In our experiments, we set both $\lambda_{\ell_1}$ and $\lambda_{\text{invariant}}$ as 0.1.

### 4.4 Network Architecture

We design our model based on the architecture introduced in [24, 60]. As illustrated in Fig. 4, our network includes an encoder of one input convolutional...
block, two downsampling blocks, and nine residual blocks to yield latent features $z$. This is followed by a decoder of two upsampling blocks and one output layer to map the features to $J$. The input convolutional block contains two convolutional layers with kernel sizes of $7 \times 7$ and $3 \times 3$ respectively. The downsampling blocks are instantiated by $3 \times 3$ convolutional layers with a stride of 2, and each upsampling block consists of a bilinear interpolation layer and a $3 \times 3$ convolutional layer. Similar to the U-Net, we fuse outputs from the downsampling blocks to their corresponding upsampling blocks via $3 \times 3$ convolutional layers to retain information lost in the bottleneck. Moreover, normal convolution layers are replaced by deformable convolution layers in our residual blocks—in doing so, we enable our model to propagate non-local spatial information to reconstruct local degradations caused by rain effects. We use batch normalization and choose leaky ReLUs with a negative slope of 0.1 as the activation function. Latent features $z$ are used for the rain-invariant loss described in Eq. (3). Since these features are high dimensional ($256 \times 64 \times 64$), we use an average pooling layer to condense the feature map of each channel to $2 \times 2$. The condensed features are flattened into a vector of length 1024 for the rain-invariant loss (see Fig. 4). It is worth noting that our rain-invariant loss does not require additional modifications on the model architectures.

4.5 Implementation Details

Our deraining model is trained on $256 \times 256$ patches and a mini-batch size $N = 8$ for 20 epochs. We use the Adam optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The initial learning rate is $2 \times 10^{-4}$, and it is steadily modified to $1 \times 10^{-6}$ based on a cosine annealing schedule. We also use a linear warm-up policy for the first 4 epochs. For data augmentation, we use random cropping, random rotation, random horizontal and vertical flips, and RainMix augmentation. Our model is implemented in PyTorch. The MS-SSIM loss is implemented based on the PyTorch Image Quality (PIQ) library. Experiments are conducted on an NVIDIA Tesla P100 GPU.

5 Experiments

We compare our method to state-of-the-art methods on GT-RAIN, both quantitatively and qualitatively, and Internet rainy images released by. To quantify the difference between the derained results and the ground-truth images, we adopt peak signal-to-noise ratio (PSNR) and structure similarity (SSIM) metrics. We first demonstrate the domain gap between synthetic and real data in Sec. 5.1 and Sec. 5.2 by testing various derainers trained on the synthetic/semi-real datasets on the GT-RAIN test set and Internet images. In Sec. 5.3, we also show that existing methods can benefit from GT-RAIN when trained from scratch on it.
5.1 Quantitative Evaluation on GT-RAIN

To quantify the sim2real gap between existing synthetic datasets, we test 7 representative existing state-of-the-art methods [46,28,22,45,19,15,55] on our GT-RAIN test set. Since there exist numerous synthetic datasets [30,52,12,56,57,28,18] proposed by previous works, we found it intractable to train our method on each one and test on GT-RAIN; whereas, we found it more feasible to take the best derainers for each respective synthetic dataset and test on our proposed dataset as a proxy. This follows the conventions of previous deraining dataset papers [11,19,30,46,53,56,57] to compare with top performing methods from each existing dataset.

SPANet [46] is trained on SPA-Data [46]. HRR [28] utilizes both NYU-Rain [28] and Outdoor-Rain [28]. MSPFN [22] and MPRNet [55] are trained on a combination of multiple synthetic datasets [30,12,52,57]. DGNL-Net [19] is trained on RainCityscapes [18]. For RCDNet [45] and EDR [15], multiple weights from different training sets are provided. We choose RCDNet [45] trained on SPA-Data [46] and EDR V4 [15] trained on Rain14000 [12] in the comparison for better performance.

Compared to training on the proposed dataset (ours, last column), methods trained on synthetic/semi-real data perform worse (Table 2), with the largest domain gap being in NYU-Rain and Outdoor-Rain (HRR) and RainCityscapes (DGNL). Two trends do hold: training on (1) more synthetic data gives better results (MSPFN, MPRNet) and (2) semi-real data also helps (SPANet). However, we note that even when multiple synthetic datasets [30,12,52,57] or semi-real dataset [46] are used, their performance on real data is still 2dB lower than training on GT-RAIN (ours).

Fig. 5 illustrates several representative derained images across scenarios with various rain appearance and rain accumulation densities. Training on GT-RAIN enables the network to remove most rain streaks and rain accumulation; whereas, training on synthetic/semi-real data tends to leave visible rain streaks. We note that HRR [28] and DGNL [19] may seem like they remove haze, but they in fact introduce undesirable artifacts into the image e.g. dark spots on the back of the traffic sign, tree, and sky. The strength of having ground-truth paired data is demonstrated by our 2.48 dB gain compared to the state of the art [55]. On test images with dense rain accumulation, the boost improves to 3.43 dB.

5.2 Qualitative Evaluation on Other Real Images

Other than the models described in Sec. [5.1] we also include EDR V4 [15] trained on SPA-Data [46] for the qualitative comparison, since it shows more robust rain streak removal results as compared the version trained on Rain14000 [12]. All the derained results on Internet rainy images are illustrated in Fig. 6. The model trained on the proposed GT-RAIN (i.e. ours) deals with large rain streaks of

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3 We use the original code and network weights from the authors for comparison. Code links for all comparison methods are provided in the supplementary material.
Table 2. Quantitative comparison on GT-RAIN. Our method outperforms the existing state-of-the-art derainers. The preferred results are marked in **bold**.

| Data Split         | Metrics | SPA Net [46] | HRR [28] | MSP FN [22] | RCD Net [45] | DGNL Net [19] | EDR V4 [15] | MPR Net [55] | Ours       |
|--------------------|---------|--------------|----------|-------------|--------------|---------------|-------------|--------------|------------|
| Dense Rain Images  | PSNR    | 18.66        | 18.87    | 17.86       | 19.58        | 19.50         | 17.33       | 18.86        | **20.89**  |
|                    | SSIM    | 0.6445       | 0.6914   | 0.5872      | 0.6342       | 0.6218        | 0.5947      | 0.6296       | 0.6375     | **0.6568** |
| Dense Rain Images  | PSNR    | 21.24        | 21.42    | 21.82       | 21.13        | 21.27         | 21.95       | 21.37        | **24.81**  |
|                    | SSIM    | 0.7768       | 0.7696   | 0.4675      | 0.7735       | 0.7765        | 0.7429      | 0.7766       | 0.7808     | **0.8262** |
| Overall            | PSNR    | 19.76        | 19.96    | 19.55       | 20.28        | 20.26         | 18.80       | 19.81        | **20.60**  |
|                    | SSIM    | 0.7012       | 0.6986   | 0.5519      | 0.6681       | 0.6552        | 0.6552      | 0.6693       | 0.7294     | **0.7294** |

Fig. 5. Our model simultaneously removes rain streaks and rain accumulation, while the existing models fail to generalize to real-world data. We select two representative scenes in the GT-RAIN test set (zoom to view details), and the associated PSNR and SSIM scores are listed at the bottom. The **red arrows** highlight the difference between the proposed method and others.
Fig. 6. Our model is capable of generalizing to other real rainy images with robust performance. We select representative real rainy images with various rain patterns and backgrounds for this qualitative (zoom to view details). EDR V4 (S) \cite{46} denotes the EDR model trained on SPA-Data \cite{46}, and EDR V4 (R) \cite{12} denotes the EDR model trained on Rain14000 \cite{12}.

various shapes and sizes as well as the associated rain accumulation effects, while preserving the features present in the scene. In contrast, we observe that models \cite{28,19} trained on data with synthetic rain accumulation introduce unwanted color shifts and residual rain streaks in their results. Moreover, the state-of-the-art method \cite{55} and top methods \cite{22,45} are unable to remove the majority of rain streaks in general as highlighted in the red zoom boxes. This demonstrates the gap between top performers on synthetic versus one that can be applied to real data.

5.3 Training Methods on GT-RAIN

We additionally train several state-of-the-art derainers \cite{46,12,55} on the GT-RAIN training set to demonstrate that our real dataset leads to more robust real-world deraining and benefits all models. We have selected the most recent derainers for this retraining study\footnote{Both DGNL-Net} \cite{19} and HRR \cite{28} cannot be retrained on our real dataset, as both require additional supervision, such as transmission maps and depth maps.
Table 3. Training comparison methods on GT-RAIN. The improvement of these derainers demonstrates the effectiveness of real paired data.

| Data Split | Metrics      | Rainy Images | RCDNet [45] (Original) | RCDNet [45] (GT-RAIN) | EDR [15] (Original) | EDR [15] (GT-RAIN) | MPRNet [55] (Original) | MPRNet [55] (GT-RAIN) | Ours         |
|------------|--------------|--------------|------------------------|-----------------------|-------------------|-------------------|----------------------|-----------------------|--------------|
| Dense Rain Streaks | PSNR↑ | 18.66 | 19.50 | 19.60 | 18.86 | 19.95 | 19.12 | 20.19 | **20.89** |
|             | SSIM↑  | 0.6445 | 0.6218 | 0.6492 | 0.6296 | 0.6436 | 0.6375 | 0.6542 | **0.6568** |
| Dense Rain Accumulation | PSNR↑ | 21.24 | 21.27 | 22.74 | 21.07 | 23.42 | 21.38 | 23.38 | **24.81** |
|             | SSIM↑  | 0.7768 | 0.7765 | 0.7891 | 0.7766 | 0.7994 | 0.7898 | 0.809 | **0.8262** |
| Overall    | PSNR↑ | 19.76 | 20.26 | 20.94 | 19.81 | 21.44 | 20.09 | 21.56 | **22.57** |
|             | SSIM↑  | 0.7012 | 0.6881 | 0.7091 | 0.6926 | 0.7104 | 0.6969 | 0.7171 | **0.7294** |

The corresponding PSNR and SSIM scores on the GT-RAIN test set are provided in Table 3. For all the retrained models, we can observe a PSNR and SSIM gain by using the proposed GT-RAIN dataset. In addition, with all models trained on the same dataset, our model comes out as the top performer in all categories.

Table 4. Runtime comparison. The average inference time is calculated on 256 × 256 color images.

| Model        | SPANet [19] (CVPR’19) | HRR [28] (CVPR’19) | MSPFN [22] (CVPR’20) | RCDNet [45] (CVPR’20) | DGNL-Net [19] (IEEE TIP’21) | EDR [15] (AAAI’21) | MPRNet [55] (CVPR’21) | Ours |
|--------------|------------------------|---------------------|-----------------------|------------------------|-----------------------------|-------------------|-----------------------|------|
| Number of Parameters | 284k                  | 40.6M               | 15.8M                 | 3.16M                  | 4.03M                       | 27.3M             | 3.63M                 | 12.9M |
| Inference Time (ms)  | 86.65                 | 35.35               | 145.5                 | 189.6                  | 4.230                       | 4.617             | 36.91                 | 12.79 |

Table 5. Ablation study. Quantitative evaluation further validates the effectiveness of the rain-invariant loss.

| Metrics | Rainy Images | Ours w/o $\mathcal{L}_{\text{invariant}}$ | Ours w/ $\mathcal{L}_{\text{invariant}}$ |
|---------|--------------|------------------------------------------|------------------------------------------|
| PSNR↑   | 19.76        | 21.69                                    | **22.57**                                |
| SSIM↑   | 0.7012       | 0.7193                                   | **0.7294**                               |

5.4 Runtime Comparison

We list the total number of parameters with the associated runtime for other state-of-the-art methods and our proposed model in Table 4. The comparison is conducted on a single NVIDIA P100 GPU, and each derainer is asked to restore a colored rainy image of size 256 × 256. We note that the top three methods (DGNL-Net [19], EDR [15], and our proposed method) all operate at real-time deraining speeds. However, our method outperforms them by 3.77 dB and 2.76 dB PSNR respectively.
5.5 Ablation Study

We validate the effectiveness of the rain-invariant loss with two variants of the proposed method: (1) the proposed network with the full objective as described in Sec. 4.3 and (2) the proposed network with just MS-SSIM loss and $\ell_1$ loss. The rest of the training configurations and hyperparameters remain identical. The quantitative metrics for these two variants on the proposed GT-RAIN test set are listed in Table 5. Our model trained with the proposed rain-invariant loss consistently outperform the one without in both PSNR and SSIM.

6 Conclusions

Many of us in the deraining community probably wish for the existence of parallel universes, where we could capture the exact same scene with and without weather effects at the exact same time. Unfortunately, however, we are stuck with our singular universe, in which we are left with two choices: (1) synthetic data at the same timestamp with simulated weather effects or (2) real data at different timestamps with real weather effects. Though it is up to opinion, it is our belief that the results of our method in Fig. 6 reduce the visual domain gap more than those trained with synthetic datasets. Additionally, we hope the introduction of a real dataset opens up exciting new pathways for future work, such as the blending of synthetic and real data or setting goalposts to guide the continued development of improved simulators.

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Supplementary Material

A Visualization of Previous Deraining Datasets

We illustrate some typical image pairs from various deraining datasets in Fig. 2.

Synthetic datasets in the community are usually generated by adding synthetic rain effects on real images taken under sunny illumination conditions, and the semi-real SPA-Data only considers rain streaks. As a result, the domain gap between these existing datasets and real rainy scenarios are relatively larger as compared with the proposed GT-RAIN dataset.

![Image of image pairs from various datasets](image)

Fig. A. GT-RAIN contains realistic rain effects (both rain streaks and rain accumulation), while the existing synthetic and semi-real datasets fail to cover the physical complexity and diversity of real-world rain. The synthetic image pair is from the commonly used Rain14000 dataset, and the pseudo ground-truth image of SPA-Data in the figure is generated by running the official code from the authors on our collected rainy video.

B More Results from GT-RAIN

As an additional supplement to Fig. 5 in the main paper, we provide some more quantitative and qualitative results from our test set in Fig. B. Note that these comparison models are using the weights provided by the authors which are trained on synthetic or semi-real datasets. We see that our proposed model trained on GT-RAIN continues to outperform other competing models.

C More Results on Internet Images

As a supplement to Fig. 6 in the main paper, we provide more qualitative results on real Internet images in Fig. C. Note that all comparison models are using the
weights provided by the author, which are trained on synthetic or semi-real datasets. All images are taken from the dataset of common real rainy images provided by [49]. Our proposed model trained on GT-RAIN continues to remove rain streaks of varying shapes and sizes as well as rain accumulation without introducing the unwanted color shifts seen in HRR [28] and DGNL-Net [19].

D Alignment of Small Motions

As a complement to Sec. 3 of the main paper, we first show, in Fig. D-(a), a ground-truth image overlayed on top of a rainy image to demonstrate representative samples that passed our data collection appearance criteria and also motion criterion, where we do not need to perform motion correction. We note that this is the case for the majority of our dataset. Additionally, we show an overlayed image pair that passed our appearance criteria, but failed the motion criterion. Fig. D-(b) shows the image pair before and after the motion correction. It should be noted that only a small portion of the data requires such correction, and our correction pipeline is designed to be robust to rain artifacts. It is because even though rain can influence local descriptors, the combinatorial matching stage is designed to be robust to a preponderance of outliers. For most cases, the percentage of outliers affects the time it takes to converge, but not the quality. All samples that require our correction procedure were manually inspected after the alignment – any failure cases of the procedure, typically due to extreme weather conditions, were manually removed.
Fig. C. More qualitative results on Internet images. Our model continues to exhibit robust generalization to real rainy images, whereas existing derainers usually fail on removing rain streaks of diverse shapes and sizes. EDR V4 (S) [15] denotes the EDR model trained on SPA-Data [46], and EDR V4 (R) [15] denotes the EDR model trained on Rain14000 [12].

E Limitations

Although we achieve the state of the art for deraining real images, our method is not perfect. Our PSNR and SSIM scores on GT-RAIN are 22.57 dB and 0.7294. This suggests that indeed, we still have ample room for improvement. For example, we leave a slight rain accumulation in the tree in Fig. C. While the recovered image is sharper and contains less rain artifacts than competing
methods, boundaries in highly textured areas (e.g. leaves, bricks, and foliage) are blurred. In Fig. C we observe a similar trend. However, this is a challenge that plagues all methods. We hope that further extensions of our approach and GT-RAIN will help mitigate these artifacts. We also do not consider occlusions from raindrops on the camera lens because the raindrops will likewise be present on the lens after the rain stops. Moreover, we do not consider specular reflections from water surfaces. This is because these reflections are nearly impossible to reconstruct as the water ripples in the puddles will destroy the visual patterns during raining. We hope that future works can address these limitations.

F Comparison Code Links

The code links for all the comparison methods are listed in Table A.

| Methods     | Links                                      |
|-------------|--------------------------------------------|
| SPANet [46] (CVPR’19) | https://github.com/stevewongv/SPANet       |
| HRR [28] (CVPR’19)   | https://github.com/liruoteng/HeavyRainRemoval |
| MSPFN [22] (CVPR’20) | https://github.com/kuljiang0802/MSPFN      |
| RCDNet [45] (CVPR’20) | https://github.com/hongwang01/RCDNet       |
| DGNL-Net [19] (IEEE TIP’21) | https://github.com/xw-hu/DGNL-Net        |
| Efficient Derain [15] (AAAI’21) | https://github.com/tsingguo/efficientderain |
| MPRNet [55] (CVPR’21)  | https://github.com/swz30/MPRNet            |
G Network Architecture

As an additional supplement of Sec. 4.4 in the main paper, we provide a detailed illustration of the network architecture in Table B.

Table B. Illustration of our network architecture.

| Network       | Kernel Size | Stride | Channels In | Channels Out | Resolution In | Resolution Out | Parameters | Input                  |
|---------------|-------------|--------|-------------|--------------|----------------|----------------|------------|------------------------|
| **Encoder**   |             |        |             |              |                |                |            |                        |
| InputConv1    | 7           | 1      | 3           | 64           | 1              | 1              | 9.5k       | Rainy Image            |
| DownConv1     | 3           | 2      | 64          | 128          | 1              | 1/2            | 74.0k      | InputConv1             |
| DownConv2     | 3           | 2      | 128         | 256          | 1/2            | 1/4            | 295.4k     | DownConv1             |
| DeformResBlock1 |           |        |             |              |                |                |            |                        |
| DeformConv11  | 3           | 1      | 256         | 256          | 1/4            | 1/4            | 652.6k     | DownConv2             |
| DeformConv12  | 3           | 1      | 256         | 256          | 1/4            | 1/4            | 652.6k     | DeformConv11           |
| Sum1          | -           | -      | 256         | 256          | 1/4            | 1/4            | Sum1 + DeformConv12   |
| DeformResBlock2 |          |        |             |              |                |                |            |                        |
| DeformConv21  | 3           | 1      | 256         | 256          | 1/4            | 1/4            | 652.6k     | Sum1                  |
| DeformConv22  | 3           | 1      | 256         | 256          | 1/4            | 1/4            | 652.6k     | DeformConv21           |
| Sum2          | -           | -      | 256         | 256          | 1/4            | 1/4            | Sum1 + DeformConv21   |
| ...           |             |        |             |              |                |                |            |                        |
| DeformResBlock9 |          |        |             |              |                |                |            |                        |
| DeformConv91  | 3           | 1      | 256         | 256          | 1/4            | 1/4            | 652.6k     | Sum8                  |
| DeformConv92  | 3           | 1      | 256         | 256          | 1/4            | 1/4            | 652.6k     | DeformConv91           |
| Sum9          | -           | -      | 256         | 256          | 1/4            | 1/4            | Sum8 + DeformConv92   |
| **Decoder**   |             |        |             |              |                |                |            |                        |
| UpConvBlock1  |             |        |             |              |                |                |            |                        |
| Bilinear1     | -           | -      | 256         | 256          | 1/2            | 1/2            | -          | Sum9                  |
| Conv11        | 3           | 1      | 256         | 128          | 1/2            | 1/2            | 295.2k     | Bilinear2             |
| Concat1       | -           | -      | 128 + 128   | 256          | 1/2            | 1/2            | DownConv1, Conv11    |
| Conv12        | 3           | 1      | 256         | 128          | 1/2            | 1/2            | 295.2k     | Concat1               |
| UpConvBlock2  |             |        |             |              |                |                |            |                        |
| Bilinear2     | -           | -      | 128         | 128          | 1/2            | 1              | -          | Conv12                |
| Conv21        | 3           | 1      | 128         | 64           | 1              | 1              | 73.9k      | Bilinear2             |
| Concat2       | -           | -      | 64 + 64     | 128          | 1              | 1              | InputConv2, Conv21   |
| Conv22        | 3           | 1      | 128         | 64           | 1              | 1              | 73.9k      | Concat2               |
| **OutputConv**|             |        |             |              |                |                |            |                        |
| OutputConv    | 3           | 1      | 64          | 3            | 1              | 1              | 1.7k       | Conv22                |

Total Parameters \( \approx 12.9M \)