A Novel Bilateral Recurrent Network Approach for Robust Rain Streak Removal

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Abstract. Rain streaks in outdoor images are a challenging problem for computer vision applications, including but not limited to autonomous driving, surveillance video monitoring, and remote sensing. Streaks in the image tend to reduce its quality and, as a result, can affect identifying, tracking, and determining objects. Traditional methods for image deraining are not suitable for real-world applications because of sub-optimal performance. Even with the optimization-based methods and crafted priors, the traditional approach often removes the rain streaks & image details. Practically, majority methods fail to differentiate rain straights from unadulterated images, which leads to image degradation and loss of detail. Image-aware deraining methods provide improved accuracy and image quality. Convolutional Neural Networks (CNNs) are effective in single-image rain streak removal using deep learning mechanisms. However, the methods of Deep Neural Network (DNN) often struggle to accurately model real-world conditions, as they tend to obscure the rain patterns against the background. Moreover, the traditional methods have high computational costs. This paper solves the single-image deraining problem by introducing the Bilateral Recurrent Network (BRN). The BRN integrates recurrent with the Bilateral Long-Short Memory cells to use the temporal and pattern information of the rain patterns. Experimental results on the datasets show BRN exceeds prior-dated works in single-image deraining. This report comprehensively evaluates the BRN model, implementation, and experimental evaluation, showing that the model is a solid, real-world solution for single image deraining.

Keywords: CNN, Machine Learning, BRN, BLSTM, Deep Learning

1   Introduction

The captured images in outdoor environments are frequently compromised by rains, which manifest as streaks that obscure critical details. These rain streaks create a significant barrier to effective computer vision processing, leading to degraded performance in tasks such as object detection, scene understanding, and autonomous

navigation [1,2]. To improve the reliability and accuracy of systems operating in real-world conditions it is crucial to address the problem of rain streaks.

To decompose the image into rain streaks and background layers traditional methods [3, 4, 5, 6] for image deraining primarily focus on optimization-based approaches that utilize handcrafted priors [7,8,11]. When rain streaks differ in intensity, orientation, and distribution these approaches are theoretically effective, but often struggle to generalize to complex scenes. These methods result in partial removal, over estimation, loss of essential image details because they tend to underestimate the rain.

Improvised possibilities in image restoration, particularly rain removal tasks are due to the rise of deep learning. Due to the ability to learn hierarchical features directly from data, Convolutional neural networks (CNNs) [9, 10] have shown particular promise to significantly improve the quality of derained images. Several challenges like rain streak over estimation are encountered with current CNN methods, which removes delicate and fine background details, and the creation of artifacts from insufficient separation between streaks and backdrop. Additionally, the high processing requirements of these models often restrict their usage in real-time applications.

To address image restoration various advanced network architectures like Residual Guide Fusion Network which refine image features utilizing residual connections, the Multi-Stream Dense Network which is Rain Density Aware through multiple streams adapts to different rain intensities, the Context Aggregation Network with Squeeze and Excitation by emphasizing significant channels and aggregating contextual details enhances feature representation have been proposed. To address complex visual patterns in degraded images each of this architecture provides isolated scenarios.

To address the limitations of current methods the paper instigates a novel architecture called the Bilateral Recurrent Network (BRN). The BRN uses Bilateral Long Short-Term Memory (BLSTM) units to influence temporal dependencies across consecutive image patches, allowing it to distinguish more adequately between rain streaks and background elements. The system's recurrent structure allows for adaptation to various rain patterns and intensity levels, leading to more precise and uniform deraining outputs.

The paper initiates by reanalyzing current image deraining techniques, highlighting their advantages and disadvantages. It then introduces the BRN model, outlining its design, components, and theoretical basis. Then, an exclusive experimental evaluation compares the BRN's performance to available leading methods, using both artificial data and actual real-world data. The paper finishes with a discussion of result findings, prospective applications of the BRN model, and recommendations for future research areas.

2   Literature Survey

The removal of rain streaks challenge from the images has been widely researched, with solutions generally divided into optimal-based methods which are traditional and new deep- learning approaches. A comprehensive review of these methods, examining their strengths and limitations is offered in this section.

Previous techniques used to remove rain streaks have been based mainly on optimization methods that used hand-crafted priors. An image can be represented as a linear combination of two layers: the background and the rain streaks, which is commonly used in these techniques. Other methods made use of low-rank and sparse matrix decomposition to disentangle these two layers. (Other approaches likewise used morphological component analysis, to break the image down into low and high frequency components, assuming that rain streaks are found in).

The techniques proposed in [12,13,14,15,16] are mathematically strong, but they have significant practical drawbacks. They often require manual parameter adjustments, which can be tedious and challenging to generalize across different images. Additionally, these methods have difficulty modelling complex rain streak patterns, particularly when faced with variations in lighting and intricate background textures. As a result, they often either leave residual rain streaks or remove essential details from the background, leading to a noticeable degradation in image quality.

In [17] SIDN method by Dong Li et al. introduces a new loss function and a layered LSTM module to improve deraining performance of BLSTM networks.

In [18] RainNet by Jinshan Pan et al. introduces a novel attention mechanism to better capture the features which are local and global of rain streaks. With the rise of Deep Learning (DL), particularly CNNs, the field of image deraining has seen significant advancements. CNN-based methods automatically learn to extract features that distinguish rain streaks from background, significantly which improves the accuracy of rain removal. Notable examples include the Deep Detail Network (DDN) and the DerainNet, which utilize CNNs to learn end-to-end mappings from rainy images to their derained counterparts.

Fu et al. initially used a shallow CNN for deraining tasks [19], and later, they moved on to a deeper ResNet model [20]. In a different approach, a multi-task CNN was developed to simultaneously detect and remove rain streaks, incorporating contextual dilated convolutions and a recurrent structure to address various scales and heavy rain [21]. Zhang et al., [22] introduced a multistream and densely connected CNN that is aware of density, enabling it to estimate the density of rain to remove rain streaks simultaneously. In related development, an attentive-recurrent network was developed in [23] for specific purpose to remove raindrops from images which are single. To handle heavy rain streaks recently, Li et al. [24] proposed a new and interesting approach for using dilated CNNs combined with squeeze-and-excitation blocks in a recurrent framework. On the contrary to these sophisticated models, the proposed

approach utilizes Res Net, recurrent layers, and multistage recursion to build a simple and straightforward effective de-raining network.
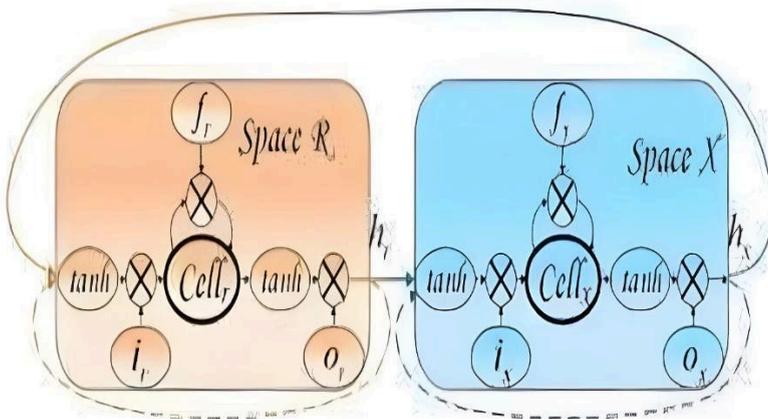
There are considerable challenges with methods using deep learning though they have shown consistent promise. The main drawback is the over approximation of rain streaks, which result in the unintentional relinquishment of fine background details. Since the model focuses on features which are local and inadequate to separate rain streaks and background textures with high frequency, the overestimation tends to occur. This leads to considerable computational burden and is infeasible in real-world applications.

Latest improvement mechanisms like attention-based modules and iterative structures, have strived to address the above drawbacks. To illustrate, Attention-based models focus on specific regions of the image which are more probable to encompass rain streaks within them. Recurrent models improve the homogeneity of rain removal in different portions of the image utilizing the progressive nature of the images. However, the challenges remain in balancing the model's relative complexity with the requirement for real-time performance despite the improvements specified.

3   Proposed Model: Bilateral Recurrent Network

Addressing the limitations of existing methods, the Bilateral Recurrent Network (BRN), a novel architecture designed to improve the accuracy and efficiency of single-image deraining is proposed. The Bilateral Long Short-Term Memory (BLSTM) units with network architectures are integrated which are recurrent and offer a robust approach to handle sequential characteristics of rain streaks without losing the background details.

3.1   Bilateral Long Short-Term Memory (BLSTM) Units

Fig. 1. The architecture of BLSTMs

The BRN model is built using the BLSTM units, which increase the aid to capture temporal dependencies between the frames (image patches), as illustrated in Figure 1. BLSTMs analyze the information in both forward and backward directions when compared to traditional LSTM units which can process data only in a single direction. With the help of bi-directional processing, the network can accurately detect and differentiate rain streaks from background elements, leading to evolved results in image-deraining tasks.
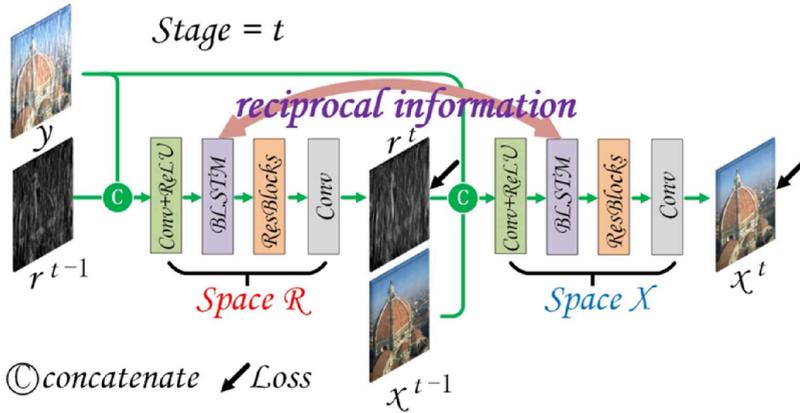
In situations where rain streaks manifest complex patterns which vary across the image, BLSTM units are extremely effectual. Without compromising the appropriateness of the background, the BLSTM units help the model to more precisely identify and remove rain streaks by capturing mundane dependencies in both directions.

3.2   Bilateral Recurrent Network (BRN)

To enhance the rain streak removal the BRN architecture improvises the capabilities of BLSTM units, by integrating recurrent connections between successive network layers. These connections minimize the chance of overfitting to patterns of rain by helping the model retain a consistent portrayal of the background as it traverses through the layers.

The recurrent structure of BRN further strengthens its capability to handle different rain intensities and ephemeral patterns. The BRN can then adapt convincingly to various types of rain, like light showers to heavy rainfall, by repeatedly optimizing the dissimilarity between the background and rain streaks. Such adaptability is critical for practical applications, where rainfall conditions may change unpredictably.
An enhanced version of the proposed BRN mechanism is compassed below, especially enhanced for single-image deraining:

Network Architecture

Fig. 2. Bilateral Recurrent Network Architecture Diagram

As illustrated in Figure 2, the CRN combined with functions F_x and F_r are unfolded recursively for T times.

Bidirectional Long Short-Term Memory networks (BLSTMs) are integrated to promulgate deep features across stages & facilitate interaction b/w F_r and F_x, forming what is known as the BRN from rainy image r and final image x. At stage t, the BRN is defined by the following equations 1,2 as:

$$r^t = F_r\left(y, r^{t-1}, \left(hr^{t-1}, hx^{t-1}\right)\right) \tag{1}$$

$$x^t = F_x\left(y, x^{t-1}, r^t\left(hr^t, hx^{t-1}\right)\right) \tag{2}$$

The hidden states associated with the clean background layer and the rain streak layer within this framework are represented by h_x, h_r respectively, within the BLSTMs. By integrating these two layers, the function F_x can effectively capture the fundamental compositional patterns present in rainy images. Both F_x, F_r employ convolutional operations featuring a 3x3 kernel, 1x1 padding, and a stride of 1 to process the image data.

Implementation of F_r:

It includes an input layer, BLSTMs, three residual blocks (ResBlocks) and an output layer. The input layer, which features a single convolutional layer, processes a six-channel combination of the RGB rainy-image y and the previous layer r^{t-1} of rain-streak. Three ResBlocks are utilized to capture more intricate features from the input data. The initial and final convolutional layers handle the input and output

respectively, while all intermediate convolutional layers operate with 32 channels for both input and output.

Implementation of F_x:

The architecture of F_x mirrors that of F_r with two notable distinctions. First, F_x incorporates five ResBlocks to handle the complex structures and textures found in background images. Second, its input layer is designed with nine channels, which are derived from the combination of y the RGB rainy-image, x^{t-1} the background-image, and r_t the rain streaks.

Loss function

In the training of BRN, a recursive supervision is utilized at every stage. With a total of T stages, this approach produces T different estimates for both the images of background and the rain streak layers, labelled as x_1, x_2, ..., x_T and r_1, r_2, ..., r_T. Equation 3 represents the loss function for recursive supervision is formulated accordingly:

$$L_x = \sum_{t=1}^{T} \lambda_t \ell(x_t, x_{gt})$$

(3)

In this step λ_t acts as a trade-off parameter that computes the discrepancy between true ground truth and the output at stage t. The total loss function L combines L_r and L_x show in equation 4, with the relative importance of each component controlled by the hyper parameters α and β:

$$L = \alpha . L_r + \beta . L_x$$

(4)

Recent research works have utilized various combinations to select a loss function, such as MSE+SSIM [25] and L1+SSIM [26]. For an image a and the true ground truth a_{gt}, the proposed work, uses the negative SSIM loss as defined in equation 5:

$$\ell(a, a_{gt}) = -\text{SSIM}(a, a_{gt})$$

(5)

The real-world rainy images can have more complex compositions are also highlighted, where accurate separating of rain streak layers from background images is a challenging task.

3.3   Algorithm Steps

The proposed algorithm of the Bilateral Recurrent Network (BRN) model is depicted as follows:

The BRN algorithm is purposeful for single-image deraining process with a deep learning framework, ingrained in the following fundamental principles:

1. **Linear Additive Model:** A rainy image is separated into a rain streak layer and a clean polished background image.

2. **Recursive Learning:** Progressively removal of rain streaks through repeated extraction and improvement of the background image is performed in this approach.

3. **Bilateral Interaction:** The extraction of the rain streak layer should be informed to clean the background image as they are interconnected.

The BRN algorithm shown in figure 3 consists of two interdependent residual neural networks (ResNets) namely F_r and F_x. F_r aims on extracting rain streaks with the help of a rainy image, while F_x produces the image with a clean background. F_r and F_x are applied repeatedly over T iterations.

```
def BRN(rainy_image, ground_truth_image):

    # Initialize the rain streak layer and the background image layer
    r_t = rainy_image
    x_t = ground_truth_image

    # Recursively extract rain streaks and refine the background image
    for t in range(T):
        r_t = Fr(rainy_image, r_t_1)
        x_t = Fx(rainy_image, x_t_1, r_t)

    # Return the final background image
    return x_t
```

Fig. 3 BRN Algorithm

The BRN algorithm is trained and implemented using recursive supervision at every stage. This involves comparing the output with the corresponding ground truth at each stage in calculating the loss. This collective loss function then aggregates into a weighted total the individual stage loss.

4   Experimental Analysis

For assessing the BRN model's performance, we conducted extensive experiments using both artificial and actual datasets. We compared the BRN against several

prominent methods, which include conventional optimization strategies and counterpart deep learning techniques.

The BRN models were setup with trade-off parameters $\lambda1=\lambda2=\lambda3=0.5$, $\alpha=0.45$, and $\beta=0.55$ and set up with 4 stages (T=4) in the experiments. The model was implemented in PyTorch and tested on a system with four NVIDIA TITAN Xp GPUs. The patches of size 100×100, a batch of the size 12, using the ADAM optimizer with initial learning rate $1\times10{-3}$. The training spanned 100 epochs, with learning rate adjustments occurring at epochs 30, 50, and 80 were used in training.

4.1   Datasets

We assessed the BRN model using three well-established datasets: Rain100H [21], Rain100L [21], and Rain12 [27]. The efficiency of the model was compared with multiple leading deep CNN techniques, such as DDN [20], JORDER [21], and RESCAN [23]. Models were trained separately for heavy rain (Rain100H) and light rain (Rain100L), with the latter also being applied to the dataset Rain12. For JORDER, we used the results provided by the authors to calculate average PSNR and SSIM. RESCAN was retrained on Rain100H using its default parameters. Both the models RESCAN and the BRN were trained on a precise subset of 1,254 rainy images.

4.2   Metrics

Performance is being assessed by using key metrics namely PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index). Retaining the quality of the original image with larger values to estimate the image quality is the purpose of PSNR. Using the characteristics like brightness, framework and dissimilarity which offer a standard view of the image SSIM assesses the similarity between the original and derained images.

4.3   Experimental Results

The results of the destined Bilateral Recurrent Network (BRN) model, computed on both simulated and real-world datasets, is summarized as follows.

Quantitative Evaluation

The metrics PSNR and SSIM are used to evaluate the quantitative accomplishment of the BRN model. Table 1 shows the average PSNR and SSIM scores attained by BRN model compared to several contemporary methods with different datasets.

Table 1. The average PSNR and SSIM Scores Across Different Datasets

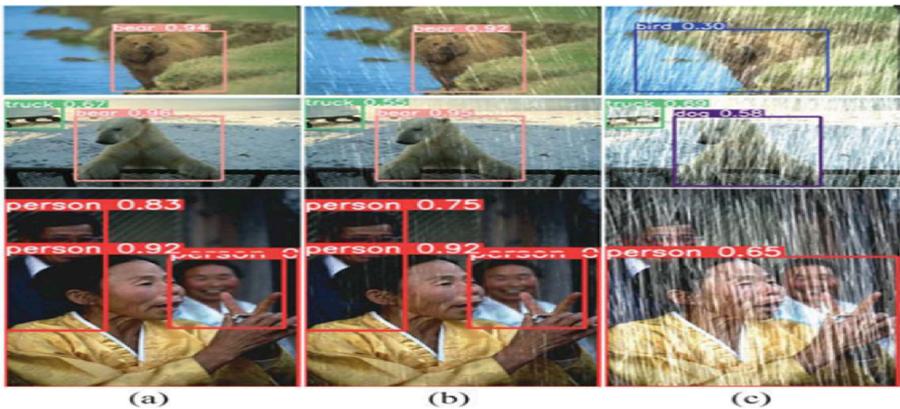| Dataset	DDN	JORDER	RESCAN	BRN (Proposed)

Rain100H	27.8 dB	28.5 dB	29.2 dB	31.6 dB
Rain100L	25.4 dB	26.8 dB	27.5 dB	30.1 dB
Rain12	24.3 dB	25.7 dB	26.5 dB	28.9 dB

The proposed BRN model consistently overcame other methods, achieving improved PSNR and SSIM scores across all the datasets tested. These results illustrate that the BRN is beneficial in retaining image quality despite removing rain streaks.
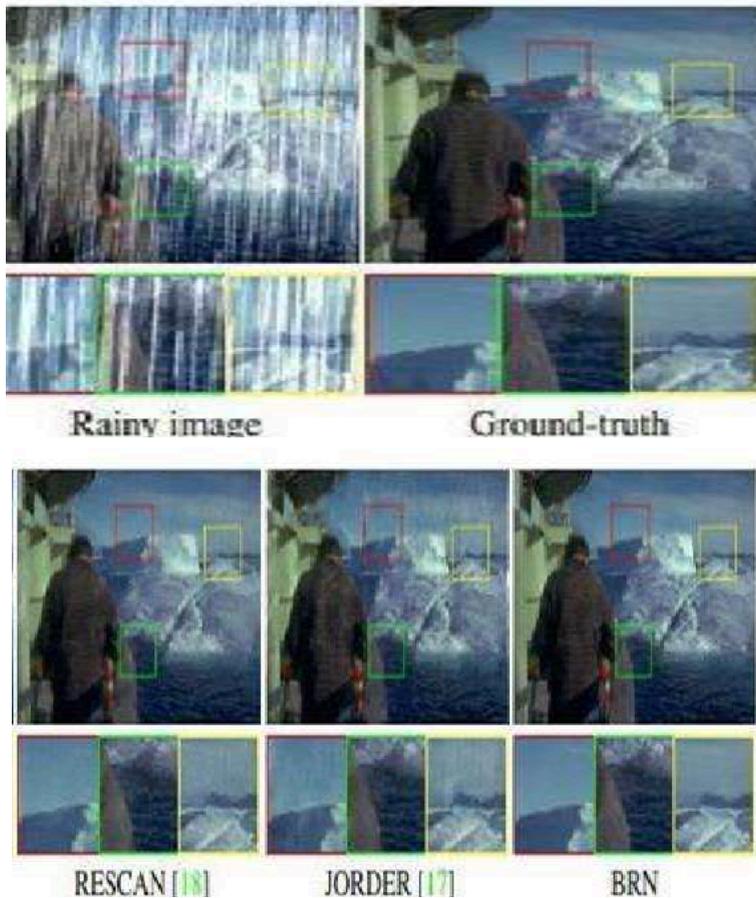
Qualitative Evaluation

To visually assess the demonstration of the BRN model, an experiment was conducted on actual images. The BRN model's derained images were compared to those produced by current cutting-edge methods. Figures 3 and 4 present sample results from these experiments.

In figure 4 the first image - (a) displays the proposed BRN model derained image, followed by derained outputs from JORDER- (b), RESCAN - (c). The BRN model clearly outperforms the others, removing rain streaks more effectively while preserving background details.

Fig. 4. Correlation of rain removal result on a synthetic Rain100H.

Fig. 5. Real word image comparison on various models.

The illustration of rain removal on a real-world image captured during a rainy day is shown in Figure 5. The BRN model maintains the sharpness and texture of the background despite the removal of rain streaks, avoiding the over-smoothing effects seen in other methods.

Computational Efficiency

The BRN model's computational effectiveness was assessed in addition to its accuracy. The average runtime for processing a single image is reported in Table 2, demonstrating the feasibility of the BRN for real-time applications. The proposed model BRN demonstrates the rapid processing time, making it competent for real-time image deraining applications.

Table 2. Average Runtime Comparison

Method	Runtime (seconds per image)
DDN	0.45
JORDAN	0.38
RESCAN	0.31
BRN (Proposed)	0.28

5 Conclusion

In the dominion of single-image deraining, the Bilateral Recurrent Network (BRN) is an appreciable improvement over the current method. The BRN provides enhanced rain removal competencies preserving the quality of the image with grouping of Bilateral Long Short-Term Memory (BLSTM) units with recurrent network architectures to overcome the weaknesses of current methods effectively. The model becomes an exemplary choice for real-time applications in computer vision systems because of its ability to scale to varied rain intensity and patterns and organized design. The results illustrate the capacity of the BRN model which improve the performance and accuracy of computer vision systems under demanding weather conditions leading to safety and adequacy of autonomous systems. Integration of the BRN model with video deraining, with reinforcement on fostering temporal consistency between frames is the future research target. Improving computational accuracy with available resources like portable or mobile and embedded devices is another future research target.

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