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Abstract. The restoration or enhancement of rainy images at nighttime is of great significance to outdoor computer vision applications such as self-driving and traffic surveillance. While image deraining has drawn increasingly research attention currently and the majority of deraining methods are able to achieve satisfying performance for daytime image rain removal, there are few related studies for nighttime image deraining, as the conditions of nighttime rainy scenes are more complicated and challenging. To address the nighttime image deraining issues, we designed an improved model based on the Syn2Real network, called NIRR. In order to obtain good rain removal and visual effect under the nighttime rainy scene, we propose a new refined loss function for the supervised learning phase, which combines the perceptual loss and SSIM loss. The qualitative and quantitative experimental results show that our proposed method outperforms the state-of-the-arts whether it is on the synthetic nighttime rainy image or on the real-world nighttime rainy image.

Keywords: Nighttime image deraining · Semi-supervised network · Gaussian Processes.

1 Introduction

Rainy images acquired at outdoor environments during daytime and nighttime, often suffer from a series of visibility degradations, e.g. obstructing and blurring background scenes, altering the object content and changing contrast and color of images, etc. Due to detail loss and signal distortion, these undesirable degradations cause visual unpleasure and seriously influence the accuracy of many outdoor computer vision applications, such as video surveillance [1, 11, 22], autonomous navigation [15], object detection and tracking [3, 18, 26]. Hence, it is important to develop effective methods that can restore or enhance rainy images.

In recent years, the issue of single image deraining has drawn increasingly research attention. Many algorithms have been developed, including the model-driven and the data-driven methods [28]. Although some satisfying performances have been achieved when dealing with daytime rainy images, but they are not suitable for night rainy scenes, as the characteristics of daytime and nighttime rainy scene are very different, the conditions of nighttime scenes are more complicated. For example, on the one hand, the nighttime image itself suffers from visibility degradation due to low ambient lighting, and the presence of rain will further seriously affect its visual quality, lead to low contrast, and limited color information. On the other hand, nighttime scenes usually have active light sources, such as street lights, car lights, and building lights. These active light sources can cause uneven lighting distribution, leading to the failure of many rain removal methods. Therefore, nighttime rainy image restoration or enhancement is more challenging.

As is known to all, the restoration or enhancement of rainy images at nighttime is of great significance to the applications such as self-driving and traffic surveillance. However, to the best of our knowledge, there is few related studies, excepting literature [20], in which Shi *et al.* developed a rainy image model to describe rainy scenes at night with low illumination and proposed a joint deep neural network-based method for single nighttime rainy image enhancement. This method achieves promising results on synthetic rainy images, but it has problems such as over-enhancement, lack of fidelity and rain residual on real-world nighttime rainy images. In the other words, it lacks the generalization capabilities to real-world image deraining. This is because, firstly, it is a fully-supervised network and it can only use fully labeled data to train, obtaining labeled real-world training data is quite challenging. Secondly, only modeling the light rainy condition might not be enough, the synthetic nighttime rainy images should contain multiple variants of nighttime rainy conditions, such as variations in scale, density and orientation of the rain streaks, to model the complex conditions of real-world nighttime rain.

Recently, Yasarla *et al.* [29] proposed a Gaussian Process-based semi-supervised learning framework (Syn2Real network) which enabled the network in learning to derain using synthetic dataset while generalizing better using unlabeled real-world images. Inspired by the success of the Syn2Real network in removing rain from images during the daytime, we improve the Syn2Real network, called NIRR, to solve the aforementioned problem of rain removal at nighttime. Similar to the Syn2Real network, our network uses semi-supervised learning, which can use unlabeled real-world rainy images for training to improve the generalization ability of real-world image deraining task. In our NIRR, we designed a new loss function composed of perceptual loss and SSIM loss for the supervised learning stage, aiming to obtain good rain removal and visual effect under nighttime rainy scenes. We have also established a new synthetic nighttime rain dataset, which contains light and heavy nighttime rain conditions, and 7 rain streak directions to simulate the complex conditions of real-world rain. Experimental results show that our method is able to effectively remove rain from nighttime rainy images.

To summarize, this paper makes the following contributions:

- An improved network based on Syn2Real network and a new synthetic nighttime rain dataset are established to address the nighttime rain removal issues.
- We adopt perceptual loss to improve the visual quality of deraining image, rather than concentrating only on the characterization of rain streaks. By simply adding SSIM loss, our method can effectively improve the overall similarity in deraining results, and it is also readily trained.

- Extensive experiments on synthetic and real rainy images demonstrate the superiority of our method in both qualitative and quantitative measures.

The rest of the paper is organized as follows. Related work is presented in Section 2. Section 3 details the proposed approach. We present the experiments and results in Section 4. Finally, Section 5 concludes the paper.

2 Related Work

In this section, we divide the single image rain removal methods into two categories: model-driven(non-deep learning) and data-driven(deep learning) ones, and discuss the existing methods of the two class in detail in the following subsections.

2.1 Model-driven Methods

Before 2017, the conventional methods are model-driven approaches, which decompose the rainy image into the rain-free background scene and the rain streaks layer, and different prior terms are designed to describe and separate the rain streak from the background layer. The major developments in the model-based approach are driven by the following ideas: sparse coding, and priors based Gaussian mixture models.

Sparse Coding Kang et al. [8] firstly proposed a single image deraining method that decomposed an input image into the low/high- frequency component using dictionary learning and sparse coding. Luo et al. [13] presented a discriminative sparse coding (DSC) over a learned dictionary for separating rain streaks from the background image based on image patches. Zhu et al. [31] constructed a joint optimization process to remove rain-streak details from the estimated background, as well as to remove non-streak details from the estimated rain streak layer using layer-specific priors. Deng et al. [4] formulated a directional group sparse model (DGSM) to model rain streak directions and sparsity, and effectively removed blurred rain streaks.

Gaussian Mixture Models Li et al. [10] utilized the Gaussian mixture models (G-MM) as a prior to decompose the input image into the rain streaks and the rain-free background layer. The traditional model-based method can achieve success in certain scenarios, however, it tends to be degenerated when applicating complicated and diverse practical rain types. Therefore, it is critical to explore more powerful coding manner for fitting general rains in real-world.

2.2 Data-driven Methods

Since 2017, the data-driven single-image rain removal method has developed rapidly and made great progress. Its development process can be summarized as: deep convolutional networks, generative adversarial networks and semi/unsupervised methods.

Deep Convolutional Networks Yang et al. [27] firstly used deep learning ideas to image deraining, they constructed a joint rain detection and removal network to detect rain locations by predicting the binary rain mask, and took a recurrent framework to remove rain streaks and clear up rain accumulation progressively. Fu et al. [5] proposed a deep detail network (DetailNet), which took only the high frequency details as input, and predicted the residue of the rain and clean images. Using the latest smoothed dilation technique and a gated subnetwork, Chen et al. [2] proposed a new end-to-end gated context aggregation network, which was initially designed for dehazing, and applied for deraining task and achieved great performance.

Generative Adversarial Networks Qian et al. [16] injected visual attention into both the generative and discriminative networks for learning to attend raindrop regions and percept their surroundings. Zhang et al. [30] directly used the multi-scale conditional generative adversarial network (CGAN) to solve single image de-raining task and obtain good results. Li et al. [9] built a two-stage single-image deraining network that combined the physics-driven network and adversarial learning refinement network.

Semi/Unsupervised Learning Methods Wei et al. [25] firstly proposed a semi-supervised learning method toward single image rain removal, which formulated the residual as a specific parametrized rain streak distribution between an input rainy image and its expected network output. Yasarla et al. [29] proposed a Gaussian Process-based semi-supervised learning framework which enabled the network in learning to derain using synthetic dataset while generalizing better using unlabeled real-world images.

In this paper, we use semi-supervised learning method to solve the problem of nighttime image rain removal because of the excellent ability to learn from synthetic and real world data.

3 Proposed Approach

Inspired by the success of Syn2Real network [29] on daytime deraining, we first adopt Syn2Real network to address the nighttime rain removal issues. In order to obtain good visual effect and quantitative scores under nighttime rainy scene, we modify the loss function for the supervised learning phase and this is the major improvement. This section presents the details of our proposed approach.

3.1 Framework

As shown in Fig. 1, our approach consists of a CNN based on the UNet structure [19], where each block is constructed using a Res2Block [6]. The same as Syn2Real network [29], the Gaussian Process (GP) is a critical step in the framework to involve iteratively training on the labeled and unlabeled data. A Gaussian Process $f(v)$ can be denoted as follows

$$f(v) \sim GP(m(v), K(v, v') + \sigma_\epsilon^2 I), \tag{1}$$

where $m(v)$ and $K(v, v')$ are the mean function and covariance function of $f(v)$, I is the

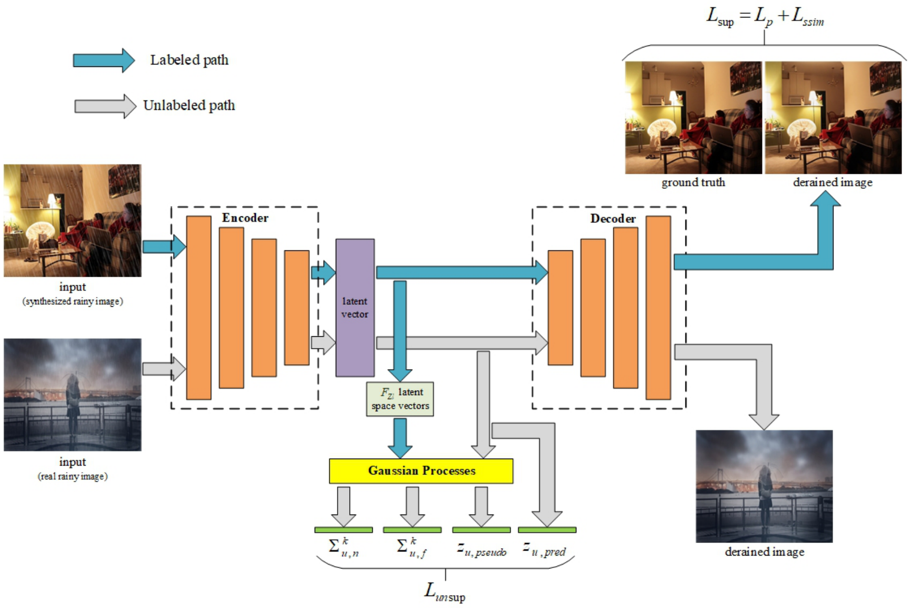

Fig. 1: The architecture of our NIRR.

identity matrix and σ_ϵ^2 is the variance of the additive noise. In Eq. 1, $v, v' \in V$ denote the possible inputs that index the GP. So, any collection of function values is then jointly Gaussian as follows

$$f(V) = [f(v_1), ..., f(v_n)]^T \sim N(\mu, K(V, V') + \sigma_\epsilon^2 I). \tag{2}$$

In our paper, a Gaussian posterior distribution in closed form is computed by conditioning on the observed data to make predictions at unlabeled points. The detailed review on GP can be found in [17, 29].

Fig. 1 shows that our NIRR is divided into two phases: labeled training phase and unlabeled training phase. The goal of our NIRR is to learn the network parameters by minimizing the supervised loss function (L_{sup}) in the labeled training phase and the unsupervised loss function (L_{unsup}) in the unlabeled training phase.

During the labeled training phase, the intermediate feature vectors z_l^i's for all the labeled training images z_l^i's are stored in a matrix F_{zl}, which is also used to generate the pseudo-GT for the unlabeled data in the unlabeled training phase. In the unlabeled training phase, GP formulation is used to generate pseudo-GT, which is used in L_{unsup}.

3.2 Loss function

In our paper, the overall loss function used for training the network is defined as follows

$$L_{total} = L_{sup} + \lambda_{unsup} L_{unsup}, \tag{3}$$

where λ_{unsup} is a predefined weight that controls the contribution from L_{sup} and L_{unsup}. And the value of λ_{unsup} is 0.0015.

From Fig. 1, L_{unsup} is a function of $z_{u,pred}$, $z_{u,pseudo}$, $\sum_{u,f}^{k}$ and $\sum_{u,n}^{k}$, as defined below

$$L_{unsup} = ||z_{u,pred}^{k} - z_{u,pseudo}^{k}||_2 + log\Sigma_{u,n}^{k} + log(1 - \Sigma_{u,f}^{k}), \tag{4}$$

where $z_{u,pred}^{k}$ is the latent vector obtained by forwarding an unlabeled input image x_u^k through the encoder, $z_{u,pseudo}^{k}$ is the pseudo-GT latent space vector, $\Sigma_{u,n}^{k}$ and $\Sigma_{u,f}^{k}$ are the variances obtained by using F_{zl}. For their expressions and specific meanings, see in [29]. The unsupervised loss function L_{unsup} in our paper is the same as in [29], and we mainly modify the supervised loss function L_{sup}.

Nighttime rainy images usually have characteristics of low contrast, uneven lighting distribution, limited color information and visual unpleasure, making the task of rain removal more challenging. The SSIM loss [24] is measured based on local image characteristics (such as local contrast, luminance and details), which are also the characteristics of rain streaks. Therefore, in our nighttime rain removal network, using SSIM loss as a part of the loss function is beneficial to the training of the supervised learning part and produces better rain removal effect. Johnson et al. [7] have shown that training with a perceptual loss measured on the early layers of VGG-16 [21] can make the model to preserve better reconstruct fine details like color, texture and shape, leading to pleasing visual result. So, in order to make our network perform well in the task of nighttime rain removal, we combine the above two loss functions into a new refined loss function L_{sup}, defined as follows

$$L_{sup} = L_p + L_{ssim}, \tag{5}$$

where L_p is the perceptual loss and L_{ssim} is the SSIM loss. L_p is the feature loss from the layer relu1_2 and relu2_2 of the VGG-16 [21]. In order to obtain more edge details from deraining image, L_1 norm is adopted in the perceptual loss L_p to minimize the distance between adjacent feature layers. Different from the negative SSIM loss in other papers, our SSIM loss L_{ssim} only needs to calculate the similarity between the deraining image B_{dr} and the corresponding ground-truth clean image B. It is defined as follows

$$L_{ssim} = 1 - SSIM(B_{dr}, B), \tag{6}$$

where $SSIM(\cdot)$ is regarded as the similarity function.

4 Experiments and Results

In this section, we present the experiments and results, including the dataset used for training and testing, evaluation metrics, and evaluation results on synthetic and real-world data.

4.1 Datasets and Metrics

Datasets The data-driven rain removal method requires a large number of training samples to obtain good performance, and the existing published datasets are used for training and testing of the daytime rain removal network. Therefore, we make a new dataset to adapt to the nighttime rainy scenes. First, we select 1200 nighttime images from ExDark [12], which has 7363 exclusively low-light images with 12 object classes captured in different time of day (e.g. twilight, nighttime), different location (e.g.

(a) Ground Truth (b) 60° (c) 70° (d) 80°

(e) 90° (f) 100° (g) 110° (h) 120°

Fig. 2: Samples of synthesized images. In the sub-picture (b)-(h), the upper picture of each image group is a synthesized light rain scene, and the lower picture is a synthesized heavy rain scene, and the orientations of the rain streaks are 60°, 70°, 80°, 90°, 100°, 110°, 120° respectively.

Fig. 3: Samples of real-world nighttime rainy images.

indoor, outdoor), and different type of light sources (e.g. the sun, man-made lights). Then, we add rain to these images using Photoshop. Each image is synthesized into 14 nighttime rainy images with two intensities (e.g. light and heavy) and 7 different orientations (e.g. 60°, 70°, 80°, 90°, 100°, 110° and 120°) respectively. So the synthesized dataset called **NiRain** contains a total of 16800 nighttime rainy images. In this synthesized dataset, we sample 9800 images as a train set, 700 images as a test set and 700 images as a validation set. Samples of synthesized images under these 14 conditions are shown in Fig 2. In addition, we have downloaded 120 real-world nighttime rainy images from the internet as a train set to better the generalization capability of our network. Fig 3 shows the samples of real-world images.

Table 1: Average PSNR and SSIM comparison (PSNR/SSIM) on the validation set. First and second best results are highlighted in color. The results of some images in the validation set are shown in Fig. 4.

Name	DSC [13]		GMM [10]		GCANet [2]		SIRR [25]		Syn2Real [29]		NIRR	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Light rain	32.0388	0.90590	35.7851	0.94773	38.9273	0.97244	36.6823	0.95881	37.2401	0.96792	38.4586	0.97768
Heavy rain	30.3937	0.81014	30.6587	0.82775	36.8971	0.95286	35.4616	0.93770	37.5588	0.96648	37.9454	0.97199

Evaluation Metrics In our experiments, two widely used metrics, namely, PSNR (Peak Single to Noise Ratio) and SSIM (Structural Similarity) [23], are adopted as the quality metrics. Generally speaking, the higher the values of PSNR and SSIM, the better the rain removal effect.

4.2 Implementation Details

In order to show the performance of our method, we implement a series of experiments on synthetic and real-world images, and compare our method with the state-of-the-art methods, such as the Discriminative Sparse Coding based method (DSC) [13] (ICCV'15), Gaussian Mixture Model (GMM) based method [10] (CVPR'16), Gated Context Aggregation Network (GCANet) [2] (WACV'19), Semi-supervised Learning method (SIRR) [25] (CVPR'19), Gaussian Process-based Semi-supervised Learning framework (Syn2Real) [29] (CVPR'20).

The proposed NIRR is implemented using Pytorch [14], and is trained on a PC with Intel Core i7 CPU 3.6 GHz, 16GB RAM and NVIDIA TITAN Xp. In our experiments, the images are randomly cropped to the size of 128×128, and the batch size is 4. Adam is used as the optimization algorithm and the models are trained for a total of 105 epochs. The learning rate starts from 0.001 and is decayed by a factor of 0.5 at every 25 epochs.

4.3 Comparison with State-of-the-Arts

Results on synthetic images In this subsection, we compare the performance of our method and other state-of-the-arts, such as DSC [13], GMM [10], GCANet [2], SIRR [25] and Syn2Real [29], on the validation set, which contains 350 synthetic rainy images at nighttime. We should note that, except for DSC [13] and GMM [10], GCANet [2], SIRR [25] and Syn2Real [29] are three deep learning methods, and are retrained with the default settings.

Quantitative results are tabulated in Table 1. As shown in Table 1, except for the PSNR in light rain condition, our NIRR obtains the best results. In order to facilitate the reader's intuitive understanding, the qualitative results are shown in Fig. 4. From Fig. 4, DSC [13] and GMM [10] retain a signification portion of rain traces after rain removal. GCANet [2] and SIRR [25] can remove majority of the rain streaks, but they still leave some rain residual. Syn2Real [29] can get a good deraining effect, but if you zoom in on Fig. 4, you can see that the first image in the sixth row still has slightly rain residual. However, our NIRR is able to preserve the details while effectively removing

Fig. 4: Qualitative comparison and PSNR/SSIM of different methods, from the first row to the last row, the displayed pictures are the synthetic rainy images, the derained results of DSC, GMM, GCANet, SIRR, Syn2Real, our NIRR and the ground truth, respectively.

the rain streaks on all the testing rainy images. We also display the PSNR and SSIM values under each derained image separately, it can also be seen that our NIRR almost achieves the highest PSNR and SSIM. So, in a conclusion, our NIRR outperforms the other state-of-the-arts, and obtains the best results on synthetic images.

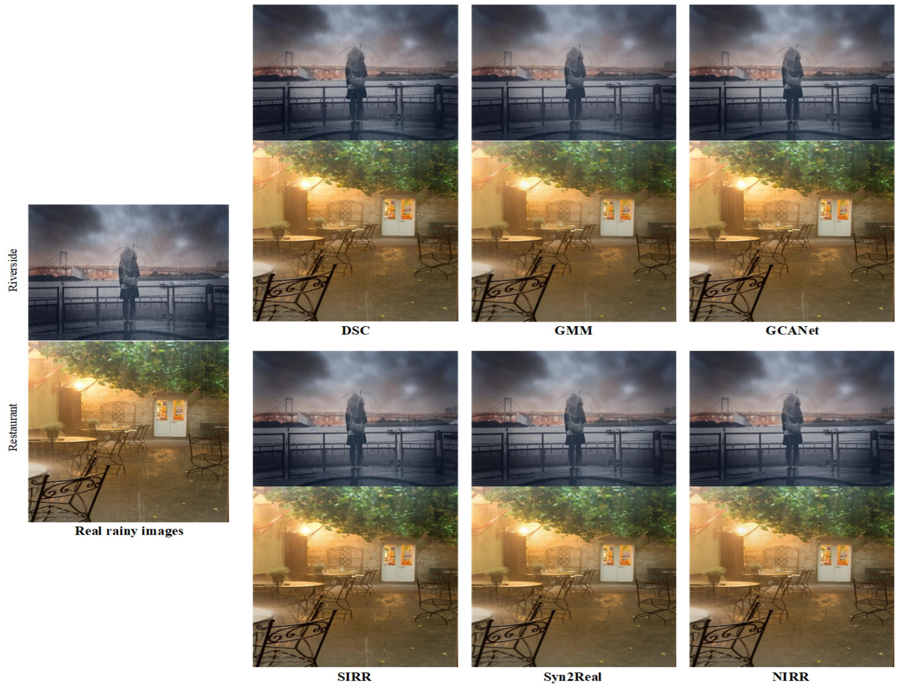

Fig. 5: Deraining results of real-world nighttime rainy images.

Results on real-world images In this subsection, two real-world rainy images in Fig. 5 are used to illustrate the effectiveness of different methods. It can be seen that the D-SC [13], GMM [10] and GCANet [2] all get undesirable rain removal effects because the traditional and supervised-learning methods are difficult to deal with the rain streaks with different scales and directions contained in real-world nighttime rainy images. Among the other three semi-supervised learning methods, the SIRR [25] method has excessive rain removal. For the real rainy image 'Restaurant', Syn2Real [29] achieves the rain removal result as good as our NIRR. However, it leaves some traces after rain removal in the image 'Riverside'. In general, our NIRR achieves the best results and image detail preservation for nighttime rain removal in real-world images.

5 Conclusions

In this paper, we design an improved model based on Syn2Real network to address the problem of nighttime image rain removal. In our NIRR, a new refined loss function for the supervised learning phase is proposed to obtain good rain removal and visual effect under nighttime rainy scene. The refined loss function is combined with perceptual loss and SSIM loss. Through the experiments on the synthesized dataset **NiRain** and real-world nighttime rainy images, our NIRR can effectively remove the rain streaks and preserve the details of deraining image compared to the state-of-the-arts.

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