DEEP LAYER PRIOR OPTIMIZATION FOR SINGLE IMAGE RAIN STREAKS REMOVAL

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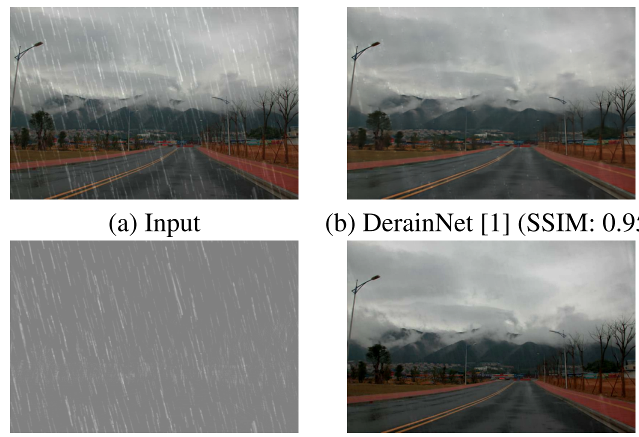
ABSTRACT

Visible distortions caused by rain streaks have significant negative effects on the performance of many vision and learning algorithms. Most of the existing deraining approaches propose to build complex prior models to formulate the appearance of rain streaks. Unfortunately, these human-designed priors tend to over-smooth the background and leave too many rain streaks since the distribution of rain streaks is complex and disordered. In this work, we exploit a deep layer prior under the maximum a posterior framework to recover the intrinsic rain structure. The optimization of the resulted variational energy can be understood as simultaneously performing rain and image propagations based on data-dependent residual networks and task cues (e.g., total variation regularization), respectively. Experimental results on both synthetic and real test images demonstrate the effectiveness of our approach against both designed priors and fully data-dependent convolutional neural networks.

Index Terms— Rain streaks removal, convolutional neural network, prior optimization, image enhancement



(a) Input (b) DerainNet [1] (SSIM: 0.95)

(c) Our rain layer (d) Our result (SSIM: 0.97)

Fig. 1. **Top row:** (a) is a challenging rainy image and (b) is a result recovered by a recently proposed deep rain removal network [1]. **Bottom row:** (c) is the rain layer extracted by our method and (d) is our recovered image. It can be seen that our method achieved better performances on both qualitative and quantitative comparisons.

1. INTRODUCTION

Most outdoor vision systems exert its effectiveness under a favorable condition. However, there are many uncertainties and unfavorable factors outdoors. As the most common bad weather condition, rain would not only reduce visibility of the image but also cause the deformation of background objects. Therefore, it is crucial to remove rain streaks from the rainy image before computer vision algorithms process it. By observing we can find the distribution of rain streaks is sparse and asymmetrical, leading it challenging to represent the rain streaks with a uniform model. Besides, rainy images are shotted outdoors surrounded by various objects, which makes it difficult to distinguish rain streaks from the complicated background structure and texture. Due to the features mentioned above, rain streaks removal appeals more and more research focuses in computer vision.

Recently, a number of single image rain streaks removal methods have been proposed. And based on the core mechanism, they are divided into two categories: conventional prior modelings and convolutional neural networks.

Conventional Prior Modelings: Kang *et al.* [2] proposed a method that decomposes the rainy image into two layers, *i.e.* high frequency layer and low frequency layer. In this way, rain streaks with background texture are assigned into high frequency layer. By performing dictionary learning, they attempts to separate the rain streaks from the high frequency layer. Although the notion is elegant, results of this method are not optimal due to its complexity. For the challenge of modeling rain streaks, the work by Li *et al.* [3] proposed to use Gaussian mixture models for both background and rain layers. By iterating the optimization equation with two different constraints, two layers can be formulated separately. Gu and Meng [4] proposed a new layer separation method which can be used in rain streaks removal by modify-

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ing the priors on two layers. It integrated the characteristics of analysis sparse representation (ASR) and synthesis sparse representation (SSR). Rainy image is decomposed into two layers, where background layer is the large-scale structure represented by ASR and rain streaks layer is the fine-scale textures approximated by SSR. But this method is inefficient.

Convolutional Neural Networks: Convolutional neural networks (CNNs) have achieved promising performance in computer vision. There are also some recent works on rain streaks removal based on deep learning. Yang *et al.* [5] modified the existing model, adding a binary map to locate rain streaks regions in the synthesis model. Moreover, they developed a multi-task deep learning architecture that learns the binary rain streaks map, appearance of rain streaks and the clean background successively. Fu *et al.* [1] utilized the knowledge of image processing to modify the object function. Similar to the idea of [2] , it also decomposes the input image into two frequency components and trains an end-to-end deep learning network between high frequency component and rain layer. The ultimate result can be obtained via integrating low frequency component and texture information. Inspired by the superiority of deep learning, the work in [6] improved the architecture of residual network, combining more ResNet blocks [7] in his network. At the same time, the training process becomes easier by reducing the mapping range. The effectiveness of this network has been improved greatly. [8] proposed a learning aggregated networks that also can be applied to rain removal. These detail networks noticeably outperform other dictionary learning and mixture modeling methods.

Although these methods have a certain effect on rainy images, there are also some shortcomings introduced by nature. For conventional prior methods, models are not applicable for the complex and irregular distribution like rain. It is difficult for models to distinguish rain with background well which makes the content information removed usually. As for deep models, their performances are tightly related to the scale and quality of the training data.

To overcome the limitations in existing approaches, we develop a novel deep prior optimization framework to gain advantages from both deep residual networks and task cues. We provide a flexible optimization method to incorporate both deep image layer priors and task cues for rain streaks and natural scene modeling. Within this framework, we design a residual type CNN to model the rain distribution based on training data. We also incorporate total variation energy to enforce our constraints on the recovered scene. In this way, we actually obtain a hybrid propagation scheme to iteratively estimate our desired scene from corrupted (by rain streaks) observation. We verify the effectiveness of our approach and compare it with state-of-the-art methods on both synthetic and real test images. Both quantitative and qualitative results demonstrate the superiority against human-designed prior models and fully data-dependent CNNs.

2. THE PROPOSED APPROACH

In this section, we present the model for single image rain streaks removal firstly, and then illustrate the proposed deep layer prior optimization with a detail analysis about it.

2.1. Basic Problem Formulation

From the point of mathematics, the input rainy image $\mathbf{O} \in \mathbb{R}^{M\times N}$ can be modeled as a linear superimposition of the desired background layer $\mathbf{B} \in \mathbb{R}^{M\times N}$ and the rain streaks layer $\mathbf{R} \in \mathbb{R}^{M\times N}$, such that: $\mathbf{O} = \mathbf{B} + \mathbf{R}$. The goal of rain streaks removal is to decompose the rain free background $\mathbf{B}$ and the rain streaks layer $\mathbf{R}$ from a given input image $\mathbf{O}$. Since this problem is ill-posed, we propose to maximize the joint probability of the background layer and rain layer using Maximum a Posteriori (MAP) which can be written as: $p(\mathbf{B},\mathbf{R}|\mathbf{O}) \propto p(\mathbf{O}|\mathbf{B},\mathbf{R}) \cdot p(\mathbf{B}) \cdot p(\mathbf{R})$ where $p(\mathbf{O}|\mathbf{B},\mathbf{R})$ delivers the likelihood of observation $\mathbf{O}$ and $p(\mathbf{B}), p(\mathbf{R})$ represent the priors of $\mathbf{B},\mathbf{R}$ on the premise that they are independent of $\mathbf{O}$. We first define the feasible solution set as:

$$\Omega = \{\mathbf{X}|0 \leq [\mathbf{X}]_{i,j} \leq [\mathbf{O}]_{i,j}, (i,j) \in [1,M] \times [1,N]\}.$$

Then we can formally formulate single image rain streaks removal as to minimize the following energy function:

$$\min_{\mathbf{B},\mathbf{R}\in\Omega} \|\mathbf{O}-\mathbf{B}-\mathbf{R}\|_F^2 + \Phi_{\mathbf{B}}(\mathbf{B}) + \Phi_{\mathbf{R}}(\mathbf{R}), \qquad (1)$$

where $\|\cdot\|_F$ represents the Frobenius norm. The first term $\|\mathbf{O}-\mathbf{B}-\mathbf{R}\|_F^2$ aims to maintain the fidelity between the input image and the recovered image. The latter two items designate the priors imposed on $\mathbf{B},\mathbf{R}$ to regularize the inference. It is worth mentioning that these two priors play a critical part in estimating credible solutions.

2.2. Deep Layer Prior Optimization

According to the Eq. (1), we use a half-quadratic optimization to solve this basic function, where we introduce two auxiliary variables $\mathbf{B}_{\mathcal{P}}, \mathbf{R}_{\mathcal{D}}$. Splitting the variables, we get the subproblems about $\{\mathbf{B},\mathbf{R}\}, \mathbf{B}_{\mathcal{P}}, \mathbf{R}_{\mathcal{D}}$ shown as Eq. (2)-(4). The proposed approach updates these variables iteratively. Since $\mathbf{B}_{\mathcal{P}}, \mathbf{R}_{\mathcal{D}}$ share the same formulation with the other variables given, implements of these two variables have nothing in common, we detail the difference in the following.

$$\begin{cases} \mathbf{R}_{\mathcal{D}} = \arg\min\limits_{\mathbf{R}_{\mathcal{D}}} \eta_{\mathbf{R}} \|\mathbf{R}-\mathbf{R}_{\mathcal{D}}\|_F^2 + \Phi_{\mathbf{R}}(\mathbf{R}_{\mathcal{D}}). & (2) \\ \mathbf{B}_{\mathcal{P}} = \arg\min\limits_{\mathbf{B}_{\mathcal{P}}} \eta_{\mathbf{B}} \|\mathbf{B}-\mathbf{B}_{\mathcal{P}}\|_F^2 + \Phi_{\mathbf{B}}(\mathbf{B}_{\mathcal{P}}). & (3) \\ \{\mathbf{B},\mathbf{R}\} = \arg\min\limits_{\mathbf{B},\mathbf{R}\in\Omega} \|\mathbf{O}-\mathbf{B}-\mathbf{R}\|_F^2 + \\ \qquad \eta_{\mathbf{B}}\|\mathbf{B}-\mathbf{B}_{\mathcal{P}}\|^2 + \eta_{\mathbf{R}}\|\mathbf{R}-\mathbf{R}_{\mathcal{D}}\|^2. & (4) \end{cases}$$

Updating $\mathbf{R}_{\mathcal{D}}$: Due to orientations and sizes of the streaks are inconsistent in an image, the distribution of rain streaks is complicated. Moreover, daedal background increases the difficulty in identifying rain streaks. Conventional prior based methods attempt to introduce a complicated model constraint to simulate rain streaks, including dictionary learning [2, 9], Gaussian mixture models (GMM) [3], but they are defective in distinguishing rain streaks from background objects, leading to an over-smooth result. Inspired by the superiority of deep learning performed in image denoising [10] and super resolution [11] where the network displays a fantastic capability in sparse regression function. Simultaneously, we observed, rain streaks emerge a sparse distribution in an image. In the Eq. (2), we do not specify the rain layer prior used in conventional prior optimization. We use a deep convolutional neural network [12, 7, 13] to perform as the rain layer prior extracting rain layer instead. And Eq. (2) can be expressed as:

$$\mathbf{R}_{\mathcal{D}} = \mathcal{D}(\mathbf{B}), \quad \mathbf{B}_{\mathcal{D}} = \mathbf{B} - \mathbf{R}_{\mathcal{D}}. \tag{5}$$

To make the network more applicable for rain removal, we reconstruct a seven layers network that consists of convolution, ReLU and batch normalization operation. The input of network is rainy image while label is rain layer. And we use the images synthetized with data from [14] to train this network.

Updating $\mathbf{B}_{\mathcal{P}}$: There are several models efficient in simulating natural scene. After network processing, a proximate rain layer can be obtained, and then utilizing the relationship between $\mathbf{O}$ and $\mathbf{B}, \mathbf{R}$, we can formulate a background layer roughly where evident streaks already have been wiped, only a little rain streaks remained in formulated background still. In this occasion, a handy and valid prior is needed to recover a clean background further. In this framework, we employ a total variation (TV) regularization based image restoration method [15, 16], in which we embody the prior item with $\|\nabla \mathbf{B}\|_1$. As a result, we turn Eq. (3) into the form as:

$$\mathbf{B}_{\mathcal{P}} = \arg\min_{\mathbf{B}_{\mathcal{P}}} \eta_{\mathbf{B}} \|\mathbf{B}_{\mathcal{D}} - \mathbf{B}_{\mathcal{P}}\|_F^2 + \rho_{\mathbf{B}} \|\nabla \mathbf{B}_{\mathcal{P}}\|_1. \tag{6}$$

This subproblem removes the trivial rain streaks further and regains the background with more edges and context information. Latent background can be enhanced efficiently.

Updating $\mathbf{B}, \mathbf{R}$: According to the Eq. (5)-(6), we can get the latent results about $\mathbf{B}_{\mathcal{P}}$ and $\mathbf{R}_{\mathcal{D}}$. Using L-BFGS algorithm [17, 18] to minimize the constraint Eq. (4) with $\mathbf{B}_{\mathcal{P}}$ and $\mathbf{R}_{\mathcal{D}}$, results of each iteration can be obtained.

To meet the need of solution space, we implement a project operation shown as Eq. (7) to ensure the estimating outputs within the scope of Ω.

$$(\mathbf{B}^+, \mathbf{R}^+) = \mathcal{P}_{\Omega\times\Omega}(\mathbf{B}, \mathbf{R}). \tag{7}$$

Above all, the proposed algorithm has been analyzed and the whole process is summarized in Alg. 1.

Algorithm 1 Deep Layer Prior Optimization

Input: Input image $\mathbf{O}$, $\eta_{\mathbf{B}}, \eta_{\mathbf{R}}, \rho_{\mathbf{B}}$, max_iter.

Initialization: $\mathbf{B} \leftarrow \mathbf{O},\ \mathbf{R} \leftarrow \mathbf{0}$.
for $k = 1 : \mathrm{max\_iter}$ **do**
    Update $\mathbf{B}_{\mathcal{P}}, \mathbf{R}_{\mathcal{D}}$ using Eq. (5)-(6);
    Update $\mathbf{B}, \mathbf{R}$ using Eq. (4);
    Update $\eta_{\mathbf{B}}, \eta_{\mathbf{R}}, \rho_{\mathbf{B}}$;
end for
Project the results into solution space Ω using Eq. (7).
Output: $\mathbf{B}^+, \mathbf{R}^+$.

3. EXPERIMENTAL RESULTS

We evaluate the performance of our proposed method on both synthetic datasets and real images, and compare it with state-of-the-art rain removal approaches, including frequency domain decomposition method (SR) [2], discriminative sparse coding method (DSC) [19], layer prior based method (LP) [3], layer separation based method (JCAS) [4] and a frequency domain CNN approach (DerainNet) [1]. As shown in Fig. 2, different values of $\eta_{\mathbf{B}}, \eta_{\mathbf{R}}$ have a limited effect on numerical result, thus we choose $\eta_{\mathbf{B}} = 0.6, \eta_{\mathbf{R}} = 0.1$ as the best parameters to execute the proposed method.

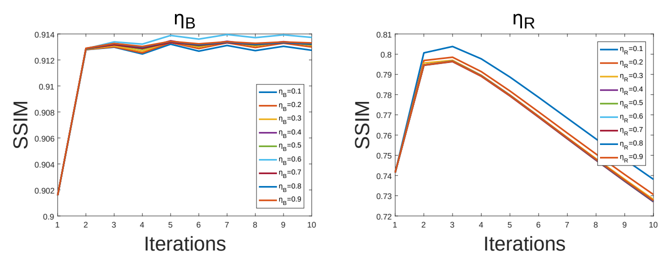


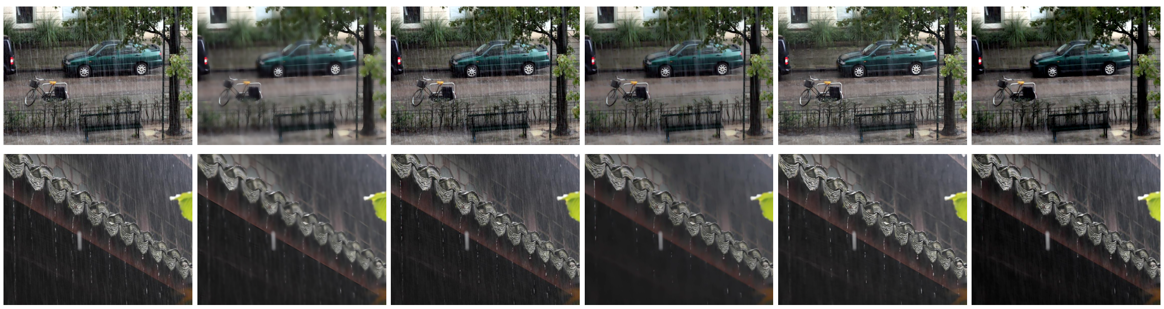
Fig. 2. The influence of $\eta_{\mathbf{B}}, \eta_{\mathbf{R}}$ in our model. We plot curves of SSIM scores with respect to $\eta_{\mathbf{B}}, \eta_{\mathbf{R}}$ during iterations.

Synthetic Data: Fig. 3 shows visual comparisons for two examples from *Rain12* database [3]. As observed in figures and the framed patches, SR [2] and LP [3] tend to over-smooth the image content, lose detail information seriously. DSC [19] fails to capture rain streaks, the effect seems not obvious. Compared with the prior methods, DerainNet [1] has a good performance on reserving background content, however little rain streaks are still remained in the results. The proposed method removes rain streaks immensely while keeping more image details in the background layer than the other methods.

Since the ground truth is known, we use the structure similarity index (SSIM) [20] for quantitative evaluation, and the results on SSIM are shown in Table.1. Because we have not got the code of JCAS [4], numerical results in this table come from the data in their paper. As can be observed, the highest value of SSIM for each image is obtained by our method,

Input | Ground Truth | SR [2] | DSC [19] | LP [3] | DerainNet [1] | Ours

Fig. 3. Visual comparisons of rain streaks removal on *Rain12* benchmark [3].



Input | SR [2] | DSC [19] | LP [3] | DerainNet [1] | Ours

Fig. 4. Visual comparisons of rain streaks removal on real images.

Table 1. Quantitative comparison of rain streaks removal results on *Rain12* [3] database using SSIM.

Rain12	1	2	3	4	5	6	7	8	9	10	11	12	Avg
SR [2]	0.72	0.80	0.83	0.75	0.65	0.74	0.81	0.76	0.74	0.74	0.60	0.75	0.74
DSC [19]	0.84	0.86	0.73	0.95	0.92	0.93	0.93	0.79	0.89	0.81	0.83	0.77	0.86
LP [3]	0.81	0.88	0.92	0.89	0.86	0.94	0.93	0.89	0.89	0.85	0.79	0.85	0.88
JCAS [4]	0.88	0.94	0.88	0.95	0.91	0.94	0.96	0.91	0.94	0.90	0.90	0.92	0.88
DerainNet [1]	0.90	0.93	0.92	**0.98**	0.94	0.97	**0.98**	**0.95**	0.94	0.91	0.91	**0.93**	0.94
Ours	**0.91**	**0.96**	**0.93**	**0.98**	**0.95**	**0.98**	**0.98**	**0.95**	**0.96**	**0.93**	**0.92**	**0.93**	**0.95**

although, there are 4 images in which our method and DerainNet [1] hold a draw. In average, our method beats the DerainNet [1], and exceeds the other methods greatly.

Real Images: Fig. 4 displays the visual results on real images. Qualitatively, SR [2] seems to over smooth background and rain streaks also be smoothed. DSC [19] fails in modeling rain layer, leaving much rain streaks in results. Although LP [3] has a better performance in removing rain streaks, it has difficulty in distinguishing rain streaks from object content, leading to a smooth background. By comparing the two real results produced by [1], we can summarize that DerainNet [1] is good at handling the long and thin rain streaks, but short for the rain column removal. The proposed method achieves the best visual results on removing visible rain streaks meanwhile preserves the most detail content. It is worth mentioning that conventional prior based methods take a large time cost to formulate rain and background, while in testing phase, our method is faster than prior methods as we replace the complicated model formulation for rain layer with network. Although our method takes a little longer than DerainNet [1], it is worth it from the perspective of effectiveness.

4. CONCLUSIONS

We have introduced a deep layer prior optimization method to address the problem of single image rain streaks removal. This method combines deep learning with conventional prior model, utilizing residual networks to extract the intricate rain layer and using a total variation regularization to enhance background layer. Compared with prior based methods, the proposed method has a stronger capacity of distinguishing rain streaks from background content, reserving more details in background. And compared with pure network methods, our method has a good performance in different rainy scenes, more robust than deep learning methods. The evaluations on both synthetic data and real images demonstrated that the proposed method achieved significant improvements in terms of effectiveness and speed, outperformed the state-of-the-arts.

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