Extended Abstract of "Heavy Rain Image Restoration: Integrating Physics Model and Conditional Adversarial Learning*

Ruoteng Li[1], Loong-Fah Cheong[1], and Robby T. Tan[1,2]

[1]National University of Singapore
[2]Yale-NUS College

Abstract

Most deraining works focus on rain streaks removal but they cannot deal adequately with heavy rain images. In heavy rain, streaks are strongly visible, dense rain accumulation or rain veiling effect significantly washes out the image, further scenes are relatively more blurry, etc. In this paper, we propose a novel method to address these problems. We put forth a 2-stage network: a physics-based backbone followed by a depth-guided GAN refinement. The first stage estimates the rain streaks, the transmission, and the atmospheric light governed by the underlying physics. To tease out these components more reliably, a guided filtering framework is used to decompose the image into its low- and high-frequency components. This filtering is guided by a rain-free residue image — its content is used to set the passbands for the two channels in a spatially-variant manner so that the background details do not get mixed up with the rain-streaks. For the second stage, the refinement stage, we put forth a depth-guided GAN to recover the background details failed to be retrieved by the first stage, as well as correcting artefacts introduced by that stage. We have evaluated our method against the state of the art methods. Extensive experiments show that our method outperforms them on real rain image data, recovering visually clean images with good details.

1. Introduction

As one of the commonest dynamic weather phenomena, rain causes significant detrimental impacts on many computer vision algorithms [11]. A series of rain removal methods have been proposed to address the problem (e.g. [5, 4, 15, 3, 13, 7, 12, 17, 8, 2, 10, 6]). Principally, these methods rely on the following model:

$$\mathbf{I} = \mathbf{J} + \sum_{i}^{n} \mathbf{S}_i, \tag{1}$$

where $\mathbf{I}$ is the observed input image. $\mathbf{J}$ is the background scene free from rain. $\mathbf{S}_i$ is the rain layer, with n as the total number of rain-streak layers.

While the model in Eq. (1) is widely used, it crudely represents the reality and we have to solve the following problems. First, we can no longer use this model since it does not accommodate rain accumulation. We need a model that can represent both rain streaks and rain accumulation, like the one introduced by [13]:

$$\mathbf{I} = \mathbf{T} \odot (\mathbf{J} + \sum_{i}^{n} \mathbf{S_i}) + (\mathbf{1} - \mathbf{T}) \odot \mathbf{A}, \tag{2}$$

where $\mathbf{T}$ is the transmission map introduced by the scattering process of the tiny water particles, $\mathbf{A}$ is the global atmospheric light of the scene. $\mathbf{1}$ is a matrix of ones, and $\odot$ represents element-wise multiplication.

Second, aside from the model, existing methods tend to fail in handling heavy rain because, when dense rain accumulation (dense veiling effect) is present, the appearance of the rain streaks is different from the training data of the existing methods [3, 14, 13]. In the real world, rain streaks and rain accumulation can entangle with each other, which is intractable to be rendered using simple physics models. Hence, a sequential process (e.g, rain-streak removal followed by rain-accumulation removal) as suggested in [7, 13] cannot solve the problem properly.

Third, particularly in heavy rain, the visual information of the background scene can be severely damaged. This is due to both rain streaks and rain accumulation as described in Eq. (2). Unfortunately, some of the damages are not represented by the model. This creates performance problems, especially for methods that rely on the model, like most of the methods do.

*This work is an extended abstract of a published paper in CVPR19."

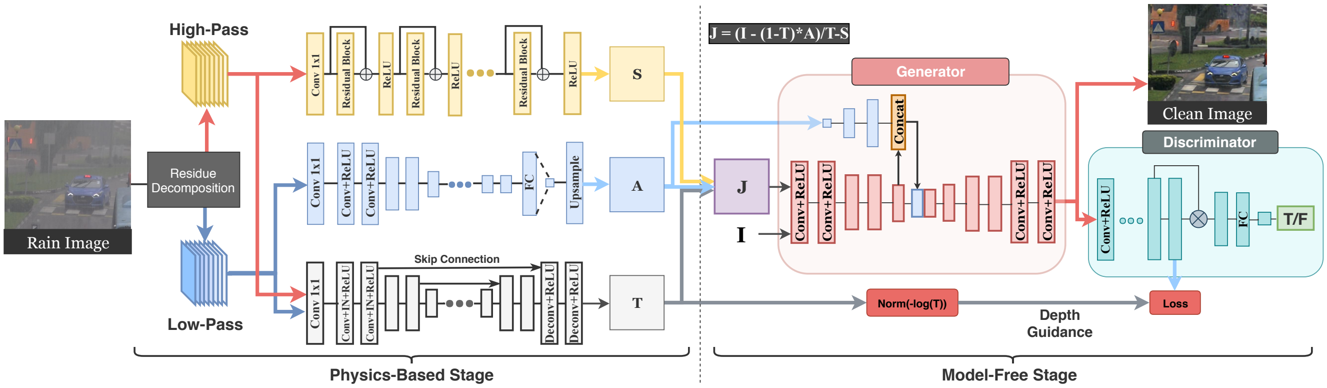

Figure 1: The overall architecture of the proposed network.

(a) Input (b) Ours (c) CycleGAN [16] (d) [1]+DID-MDN [14] (e) RESCAN [6] + [1] (f) Reference

Figure 2: A comparison of our algorithm with baseline methods on real-world rain scenes. The reference images are other pictures taken just after rains. From top to bottom, the rain becomes more and more severe. (Zoom-in to view details).

2. Method

To address these existing problems resulted by heavy rain, we introduce a novel CNN method to remove rain streaks as well as rain accumulation simultaneously with the following contributions:

(1) We introduce an integrated two-stage neural network: a physics-based subnetwork and a model-free refinement subnetwork, to address the gap between physics-based rain model and real rain. The first stage estimates **S**, **A**, **T** and produces reconstructed image **J** strictly governed by the rain model. The second stage contains a conditional GAN (cGAN) [9] that is influenced strongly by the outputs of the first stage as shown in Fig. 1.

(2) We propose novel streak-aware decomposition to adaptively separate the image into high-frequency component containing rain streaks and low-frequency component containing rain accumulation. This addresses the problem of entangled appearance of rain streaks and rain accumulation. Also, since we can have a low frequency component, we can utilize it to resolve the problem of estimating the atmospheric light, **A**.

(3) We provide a new synthetic data generation pipeline that synthesizes the veiling effect in a manner consistent with the scene depth. For more realism, we also add Gaussian blur on both the transmission map and the background to simulate the effect of scattering in heavy rain scenarios.

3. Experimental Results

Fig. 2 shows the qualitative comparison between our method and other baseline methods. In the case of heavy rains, these baseline methods fail to remove the rain streaks effectively due to the presence of strong rain accumulation. In addition, the state of the art haze removal method cannot effectively remove the veiling effect. One can still observe hazy effect at the remote area of the baseline results. Thanks to the depth guided GAN, our method is able to identify the remote areas and remove the proper amount of veiling effect.

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