SINGLE IMAGE DE-RAINING USING DEEP DECOMPOSITION- COMPOSITION NETWORK

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Abstract— Under rainy conditions the impact of rain streaks on images and video is often undesirable. The effects of rain can also severely affect the performance of outdoor vision system. The quality of the image is degraded by rain streaks. Hence it is necessary to remove rain streaks from single image which is a challenging problem. Towards fixing this problem the deep decomposition- composition network is proposed. This paper designs a novel multi-task leaning architecture in an end-to-end manner to reduce the mapping range from input to output and boost the performance. Concretely, a decomposition net is built to split rain images into clean background and rain layers. Different from previous architectures, this model consists of, besides a component representing the desired clean image, an extra component for the rain layer. During the training phase, further employ a composition structure to reproduce the input by the separated clean image and rain information for improving the quality of decomposition. Furthermore, this design is also applicable to other layer decomposition tasks like dust removal. More importantly, this method only requires about 50ms, significantly faster than the competitors, to process a testing image in VGA resolution on a GTX 1080 GPU, making it attractive for practical use.

Index Terms- Decomposition- composition network, Video Graphics Array, Graphics Processing Unit.

INTRODUCTION

Rain removal is a complex task. In rainy image pixels exhibit small but frequent intensity fluctuations and this fluctuation could be caused by several other reasons besides rain fall namely global illumination change, camera move and object motion etc. In order to remove the rainy effect, it is necessary to detect the fluctuations that are caused by rain and then replace them with their original value.

The impact of rain weather in the images will make it complicated to distinguish in the environment surroundings using an outdoor camera. Moreover, single image plays important role in numerous areas such as in object recognition and detection, enhancement, noise removal and weather condition removal. Rainy weather of outdoor images and videos reduces the visibility, performance of computer vision algorithms and other outdoor activities, which use for extracting features and information from images.

Visual distortions on images caused by bad weather conditions can have a negative impact on the performance of many outdoor vision systems. One of the bad weather is rain which causes significant yet complex local intensity fluctuations in images. Most computer vision tasks assume the sufficient high quality of images. However, various degradations often occur in realistic scenes. For example, rainy weather becomes an inevitable situation when these tasks are applied to outdoor scenes. The rain in image can be roughly divided in to two cases. Rain streaks near to the camera lens can be considered as noise in the image, whereas rain from long distance looks like fog.

Rain streak removal is an important issue in outdoor vision systems. There are many situations in which images or video might be captured through a window. A person may be inside a car, train or building and wish to photograph the scene outside. Indoor situations include exhibits in museums displayed behind protective glass. Such scenarios have become increasingly common with the widespread use of Smartphone cameras. Beyond consumer photography, many cameras are mounted outside, e.g. on buildings for surveillance or on vehicles to prevent collisions. These cameras are protected from the elements by an enclosure with a transparent window. Such images are affected by many factors including reflections and attenuation.

Most, if not all, of classic and contemporary vision-oriented algorithms, such as object detection [17] and tracking [28], can work reasonably well when facing images of high visibility, but dramatically degenerate or even fail if they are fed with low-quality inputs. In real-world scenarios, especially for outdoor scenes, rain effect has always been such an annoying and inevitable nuisance, which would significantly alter or degrade the content and color of images [16]. These situations frequently occur if one records an event happening at a square using a smart phone, a surveillance camera monitors a street, or an autonomous vehicle drives on a road, in rainy days. The rain in atmosphere generally has two existence styles, say steady rain and dynamic rain. The steady rain is caused by distant microscopic rain drops globally accumulated through- out the scene, while the dynamic one comes from large particles (rain streaks) that look like random local corruptions. The left column of Fig. 1 gives two such examples. For eliminating or reducing negative effects brought by rain, the development of effective approaches is demanded. Formally, the rainy image can be seen as a superimposition of two layers $O = \Psi R + B$, where $O \in \mathbb{R}^{m \times n}$ designates the observed data and, $R \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{m \times n}$ represent the rain layer and the desired clean background, respectively.
II. PREVIOUS ARTS AND CHALLENGES

Over the past decades, a lot of attentions to resolving the rain removal problem have been drawn from the community. From the perspective of required input amount, existing rain removal methods can be divided into two classes, i.e. multi-image based and single image based methods. Early attempts on deraining basically belong to the former category. A representative solution was proposed in [6], based on the recognition that the visibility of rain in images depends much on the exposure time and depth of field of the camera. One can achieve the goal by testing on several images and adjusting the operational parameters of the camera. But this method is too professional to use for typical consumers. The work in [7] employs two constraints to automatically find and exclude possible rain streaks, and then fills up the holes by averaging the values of their temporal neighbors, which releases the professional requirement. Several follow-ups along this technique include [30] and [26] try to improve the accuracy of rain streak detection or/and the quality of background inpainting. A more elaborated review on the multi-image based rain streak removal approaches can be found in [20]. Generally, this kind of methods can provide reasonable results when the given information is of sufficient redundancy, but this condition is often violated in practice.

For the sake of flexibility and applicability, single image based approaches are more desirable but challenging. Kang et al. [11] proposed a two-step method. The first step is separating the input rain image into a low-frequency component containing its structure and a high-frequency one with both rain streaks and background textures. Then the image textures are distinguished from the rain streaks in the detail layer according to constructed dictionaries, and added back to the structure layer. However, the separation in the detail layer is challenging, always tending to either oversmooth the background or leave noticeable rain streaks. Its follow-ups include [10, 19]. Chen and Hsu [2] proposed a unified objective function for rain removal by exploring the repetitive property of the rain streak appearance and using a low rank model to regularize the rain streak layer.

fins is problematic as other repetitive structures like building windows also fit the low-rank assumption. Kim et al. [12] tried to detect rain streaks by a kernel regression method, and remove the suspects via a nonlocal mean filtering. It frequently suffers from inaccurate detection of rain streaks. Luo et al. [14] created a new blending model and attempted to reconstruct the background and rain layers of image patches over a self-trained dictionary by discriminative sparse coding. Although the method has an elegant formulation, the blending model used still needs physical validation and the effectiveness in removing the rain is somehow weak as one can always see remaining thin structure at the rain streak locations in the output. Li et al. [13] used patch-based priors for both the two layers, namely a Gaussian mixture model (GMM) learned from external clean natural images for the background and another GMM trained on rain regions selected from the input image itself for the rain layer. These prior-based methods even with the help of trained dictionaries/GMMs, on the one hand, are still unable to catch sufficiently distinct features for the background and rain layers. On the other hand, their computational cost is way too huge for practical use.

With the emergence of deep learning, a number of low-level vision tasks have benefited from deep models supported by large-scale training data, such as [21, 29] for denoising, [3] for super-resolution, [4] for compression artifact removal and [1] for dehazing, as the deep architectures can be leveraged with explicit and implicit features. As for deraining, Fu et al. proposed a deep detail network (DDN) [5], inspired by [11]. It first decomposes a rain image into a detail layer and a structure layer. Then the network focuses on the high-frequency layer to learn the residual map of rain streaks. The restored result is formed by adding the extracted details back to the structure layer. Yang et al. [23] proposed a convolutional neural network (CNN) based method to jointly detect and remove rain streaks from a single image (JORDER). They used a multi-stream network to capture the rain streak component with different scales and shapes. The rain information is then fed into the network to further learn rain streak intensity. By recurrently doing so, the rain effect can be detected and removed from input images. The work in [27] proposes a single image de- raining method called image deraining conditional general adversarial network (ID-CGAN), which considers quantitative, visual and also discriminative performance into the objective function. Tough the deep learning based strategies have made a great progress in rain removal compared with the traditional methods, two challenges still remain:

- How to enhance the effectiveness of deep architectures for better utilizing training data and achieving more accurate restored results.
- How to improve the efficiency of processing testing images for fulfilling the high-speed requirement in real-world (real-time) tasks.

III. PROPOSED METHOD

In order to address the above mentioned challenges, a novel deep decomposition-composition network (DDC-Net) was proposed to effectively and efficiently remove the rain effect from a single image under various conditions. Concretely, the contributions can be summarized as follows. The designed network is composed by a decomposition net and a composition net. The decomposition net is built for splitting rainy images into clean background and rain layers. The
volume of model is retained small with promising performance. Hence, the effectiveness of the architecture is boosted. The composition net is for reproducing input rain images by the separated two layers from the decomposition net, aiming to further improve the quality of decomposition. Different from previous deep models, ours explicitly takes care of the recovery accuracy of the rain layer. During the testing phase, only the decomposition net is needed. The designed network architecture is illustrated in Fig. 2. It consists of two modules, i.e., the decomposition network and the composition network.

A. Decomposition Net

As can be seen from Fig. 2, the decomposition network, aiming to separate the rain image into the clean background and rain layers, has two main branches: one focuses on restoring the background and the other for the rain information.

Inspired by the effectiveness of encoder-decoder networks in image denoising [15], inpainting [18] and matting [22], decomposition branch based on the residual encoder and decoder architecture with specific designs for clean background and rain layer prediction are constructed as follows: 1) the first two convolutional layers in the encoder are changed to dilated convolution [24] to enlarge the receptive field. The stride of our dilated convolutional layer is \( 1 \times 1 \) with padding. Max-pooling to down-sample feature maps is used. 2) Two decoder networks is used to recover the clean background and rain layer respectively; and 3) features from the deconvolution module of the clean background branch are concatenated to the auxiliary rain branch for better obtaining rain information during the up-sampling stage.

\[
O = B + R.
\]

There are other factors in rainy images, such as haze and splashes. To solve this problem, first concatenate the clean background image and the rain layer from the decomposition network, and then adopt an additional CNN block to model the real rainy image formulation. The proposed composition network could achieve a more general formation process and accounts for some unknown phenomenon in real images.

IV EXPERIMENTS AND RESULTS

This section evaluates DDC-Net on the task of rain removal, in comparison with the state-of-the-arts including GMM [13], JORDER [23], DDN [5] and ID-CGAN [27]. For quantitatively measuring the performance, employ PSNR, SSIM and elapsed time as the metrics.

A. Synthetic Data

First synthesize 7 rainy images, which are shown in the top row of Fig. 3. Table I lists the values of PSNR and SSIM of all the competitors. From the numerical results, we can see that, except for the first case (PSNR and SSIM) and the fifth case (SSIM only), proposed DDC wins over the others by large margins. While, in the first case, DDC slightly falls behind DDN by about 0.33 in PSNR and in SSIM, but is still superior to the rest techniques. Figure 3 provides two visual comparisons between the methods, from which we can observe that the DDC can produce very striking results.

![Figure 2: Proposed Architecture](image)

**Figure 2:** Proposed Architecture

**B. Composition Net**

Our composition net aims to learn the original rainy image from the outputs of decomposition model, then use the constructed rainy image as the self-supervised information to guide the back-propagation. With the decomposition model, we can disentangle a rainy image into two corresponding components. The first one is the recovered rain-free image \( B \) from the clean background branch. The second one is the rain layer, denoted as \( R \), learned by the auxiliary rain branch. Therefore, the rain image \( O \) is directly composed in a simple way:

![Figure 3: Top row shows the synthetic images used in the quantitative evaluation. The rest row give two comparisons.](image)

**Figure 3:** Top row shows the synthetic images used in the quantitative evaluation. The rest row give two comparisons.

\[ a) \text{GMM} \quad b) \text{JORDER} \quad c) \text{DDN} \quad d) \text{ID-CGAN} \quad e) \text{Without composition network} \quad f) \text{DDC} \quad g) \text{Groundtruth} \]
GMM leaves rain streaks in both the outputs. For ID-CGAN, it not only suffers from ineffectiveness in rain removal but also alters the color, making the results unrealistic. DDN performs reasonably well for the upper image but not for the lower one, while JORDER produces a good result for the lower image but unsatisfactory for the upper one. In addition, with the composition net disabled, the decomposition net can still largely separate the rain effect from the inputs. By the complete DDC-Net, the results are further boosted and quite close to the ground truth.

v. CONCLUSION

This paper has proposed a novel deep architecture for single image rain removal, namely the deep decomposition-composition network, which consists of two main sub-nets including the decomposition network and the composition network. The decomposition network is built to split rain images into clean background and rain layers. Different from previous networks, the composition model consists of a component representing the desired clean image, an extra component for rain layer. During the training phase, the additional composition structure is employed to reproduce the input by the separated clean image and rain information for further boosting the quality of decomposition. Experimental results on both synthetic and real images have been conducted to reveal the efficiency of the design, and demonstrate its clear advantages in comparison with other state-of-the-art methods. In terms of running time, proposed method is significantly faster that the other techniques, which can broaden the applications to single image denoising.

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