A Decomposed Dual-Cross Generative Adversarial Network for Image Rain Removal

Xin Jin Student
jinxustc@mail.ustc.edu.cn
Zhibo Chen Prof
chenzhibo@ustc.edu.cn
Jianxin Lin Student
linjx@mail.ustc.edu.cn
Jiale Chen Student
chenjlcv@mail.ustc.edu.cn
Wei Zhou Student
weichou@mail.ustc.edu.cn
Chaowei Shan Student
cwshan@mail.ustc.edu.cn

CAS Key Laboratory of Technology in Geo-spatial Information Processing and Application System
University of Science and Technology of China
Hefei 230027, China

Abstract

Rain removal is important for many computer vision applications, such as surveillance, autonomous car, etc. Traditionally, rain removal is regarded as a signal removal problem which usually causes over-smoothing by removing texture details in non-rain background regions. This paper considers the issue of rain removal from a completely different perspective, to treat rain removal as a signal decomposition problem. Specifically, we decompose the rain image into two components, namely non-rain background image and rain streaks image. Then, we introduce an adversarial training mechanism to synthesize non-rain background image and rain streaks image in a Dual-Cross manner, which makes the two adversarial branches interact with each other, archiving a win-win result ultimately. The proposed Decomposed Dual-Cross Generative Adversarial Network (DDC-GAN) shows significantly performance improvement compared with state-of-the-art methods on both synthetic and real-world images in terms of qualitative and quantitative measures (over 3dB gains in PSNR).

1 Introduction

Unpredictable rainy conditions adversely affect the performance of many outdoor vision systems and cause them to likely fail especially in heavy rain, such as surveillance, autonomous car, etc. Effective methods for removing rain streaks are needed for a wide range of practical applications.

As a low-level image processing problem, rain removal is challenging due to the complex appearance of natural scenes and the motion dynamics of rain streaks. Traditional methods are usually suffered from the over-smoothing effect due to its inherent perspective of regarding the issue as a signal removal problem [2, 7, 15, 21].

Instead, this paper tries to understand the issue from a completely new perspective of signal decomposition and proposes an end-to-end learning based model named Decomposed Dual-Cross Generative Adversarial Network (DDC-GAN) and demonstrates its effectiveness in rain removal problem.

2 Related Work

A lot of efforts have been dedicated towards rain removal in the past decades and almost all these solutions model the problem as a basic signal removal problem. These methods generally fall into two categories: video based and single-image based methods. Some research works focus on recovering rain image from video sequences [2, 4, 7] by leveraging more prior information, such as spatiotemporal correlation. Image rain removal problem is usually more challenging without temporal context information and can be further classified into after-mentioned two categories.

Traditional single-image based methods usually try to use different mathematical models to describe the non-rain background and the rain streaks image separately [11, 15, 21]. Recently, some single-image based rain removal algorithms model this problem as a layer separation task. Luo *et al.* [21] use a discriminative sparse coding method to recover a clean image from background images. Huang *et al.* [15] propose to separate the rain streaks from the high frequency layer by sparse coding, with a learned dictionary. Li *et al.* [17] exploit the Gaussian mixture models to separate the rain streaks, and patch-based priors are used for both a clean layer and a rain layer, which still remain residual rain and block artifacts in the synthesized background, i.e. rainy artifacts.

The renaissance of **deep neural network** (DNN) remarkably accelerates the progress of image processing applications [1, 3, 19, 22, 23]. [5] tries to propose CNN-based rain removal solution but gets unsatisfactory results. Recently, inspired by ResNet [10], Fu *et al.* [6] simplified the learning process by changing the mapping form, and focusing on high-frequency details during training. Yang *et al.* [27] proposed a deep recurrent rain removal network to remove rain streaks progressively, which achieves the state-of-the-art performance even in the presence of heavy rain and rain streak accumulation. However, such a mechanism containing redundant convolution operations may still causes over-smoothness and blur artifacts in the background.

In general, there still exists obvious over-smoothness and rainy artifacts in non-rain regions due to the intrinsic overlapping between rain streaks and background texture patterns in traditional signal removal frameworks. Therefore, we propose a Decomposed Dual-Cross Generative Adversarial Network (DDC-GAN) for single-image rain removal, which can remove rain streaks as clean as possible while keeping the details of the no-rain background intact. The contributions of this work are summarized as follows:

- We redefine the problem of single-image rain removal from the perspective of signal decomposition and decomposed the model into two components (one for background, the other for rain streaks) while preserving domain independent features. This unique decomposed structure guarantees both the texture details of synthesized background and rain streaks.

- For each component, we adopt a dual-cross adversarial learning mechanism to make both the results of background and rain streaks indistinguishable from reality. Different from simple dual learning frameworks [9, 18, 28], we introduce a concept of

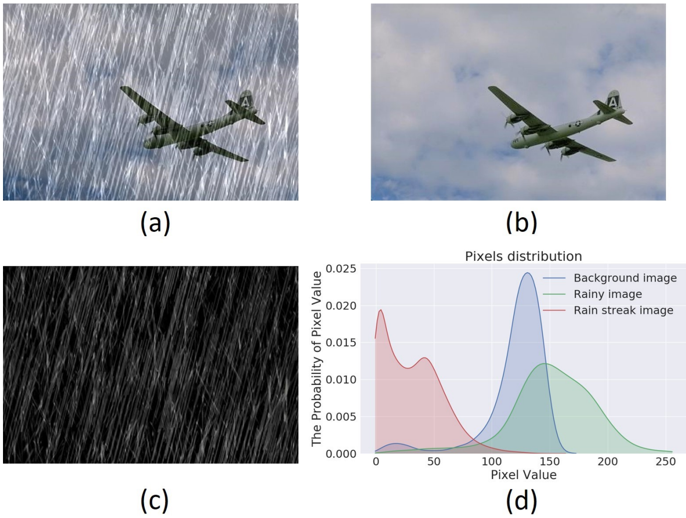

Figure 1: Different images and corresponding histograms. (a) Rainy image; (b) Background image; (c) Rain streak image; (d) Histograms of above images.

dual-cross adversarial learning where the background synthesized by one generator has the ability to help the other generator infer realistic rain streaks, while the synthesized rain streaks in turn lead to realistic background, and then achieve a win-win result.

- To the best of our knowledge, it is the first paper to successfully introduce GAN [8, 13, 16, 24, 25, 29] to decrease the blur artifacts in de-rained images generated by conventional networks with hallucinatory synthesis schemes.

- We train the network on synthetic data since the ground truth clean images corresponding to real-world rainy images can not be publically available. We then show that the learned network has strong generalization ability to deal with real-world test images. Experimental results also demonstrate that our proposed DDC-GAN outperforms existing methods.

3 Decomposed Dual-Cross GAN (DDC-GAN)

We illustrate the proposed DDC-GAN framework in Figure 2. We will first briefly discuss the statistical histograms of background image B and rain streaks image R in 3.1, and conclude from the analysis that they can be modeled separately from the perspective of signal decomposition. Subsequently, we introduce our core ideas, network structure and mechanisms in 3.2 and 3.3.

3.1 Analysis and Modeling

To improve the synthetic results, it is important to make the model to learn the regression function well. This requires that the distribution of the input signal is consistent with the distribution of the target. As shown in Figure 1, we observe that background image B, rainy image I, and rain streaks image R ($R = I$ - B) have significant differences in pixel value distributions. This implies that it is possible to decompose B and R into two separate components, and achieve the successful regression for synthesized B and R separately. Therefore we proposed a decomposed structure to decompose image R and image B separately.

3.2 Decomposed Structure

As described above, each component of the model corresponds to a generator as shown in Figure 2. A rainy image I is first fed into two mutually independent generator G_B and G_R to generate synthesized background $\widehat{B}$ and rain streaks $\widehat{R}$, respectively. Then, the two generators swap positions to form a dual-cross structure as the orange dotted arrows denoted in Figure 2, G_B receives the residual of I - $\widehat{R}$ and G_R receives the residual of I - $\widehat{B}$ as input again. This implies that this dual-cross operation assists G_B to learn a regression function from $\widehat{B}$ to $\widetilde{B}$ (I - $\widehat{R}$), G_R from $\widehat{R}$ to $\widetilde{R}$ (I - $\widehat{B}$). Intuitively, the two generators form a closed loop, generating informative feedback signals through interactive objective function to each other for better convergence, which makes both synthesized background $\widehat{B}$ and $\widetilde{B}$ simultaneously close to the real one, and for $\widehat{R}$ and $\widetilde{R}$ as well.

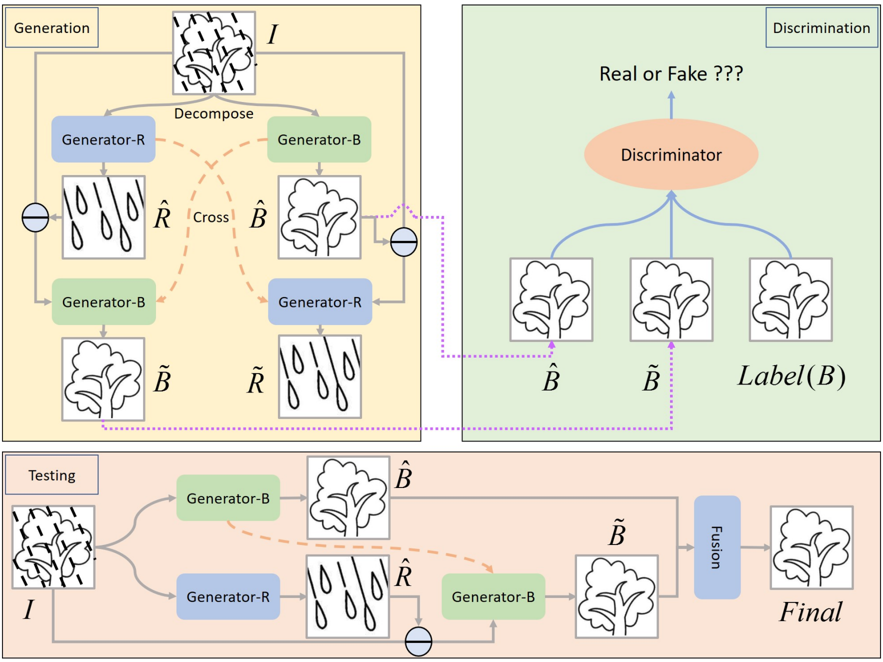

Figure 2: The structure of our proposed DDC-GAN. The testing stage is shown in the bottom row and the other part is training stage.

3.3 Dual-Cross Adversarial Training Mechanism

In addition to the unique decomposed structure, we also leverage the dual learning techniques and GAN theories to jointly optimize the DDC-GAN and restrict it from the perspective of signal decomposition, which is achieved by a set of loss functions shown as below. The whole optimization process as pseudo code in Algorithm 1.

Algorithm 1 DDC-GAN training process

Require: Training inputs and labels $\{I_i\}_{i=1}^N \subset \mathcal{D}_{input}$, $\{B_j\}_{j=1}^N \subset \mathcal{D}_{background}$, $\{R_m\}_{m=1}^N \subset \mathcal{D}_{rain}$, batch size K, optimizer $Opt(\cdot,\cdot)$;

1: Randomly initialize G_B, G_R, D.

2: Randomly sample a minibatch of images and prepare the data pairs $\mathcal{S} = \{(I_k, B_k, R_k)\}_{k=1}^K$.

3: Update the two decomposed generators as follows:
No.1 step: For any data pair $(I_k, B_k, R_k) \in \mathcal{S}$, generate first-step synthesis $\widehat{B_k}, \widehat{R_k}$ by Eq.(1), and constitute the MSE loss function by Eq.(2);
No.2 step: The two generators G_B, G_R swap their position to form a dual-cross structure, generate second-step synthesis $\widetilde{B_k}, \widetilde{R_k}$ by Eq.(3), and constitute the MSE-cross loss function by Eq.(4);
No.3 step:
$G_B \leftarrow Opt(G_B, (1/K)\nabla_{G_B}\sum_{k=1}^K \ell_{\text{MSE}}(\widehat{B_k}, B_k))$,
$G_B \leftarrow Opt(G_B, (1/K)\nabla_{G_B}\sum_{k=1}^K \ell_{\text{MSE-cross}}(\widetilde{B_k}, B_k))$,
$G_R \leftarrow Opt(G_R, (1/K)\nabla_{G_R}\sum_{k=1}^K \ell_{\text{MSE}}(\widehat{R_k}, R_k))$,
$G_R \leftarrow Opt(G_R, (1/K)\nabla_{G_R}\sum_{k=1}^K \ell_{\text{MSE-cross}}(\widetilde{R_k}, R_k))$;

4: Update the discriminators as follows:
$D \leftarrow Opt(D, (1/K)\nabla_D\sum_{k=1}^K \ell_{\text{GAN}}(\widehat{B_k}, \widetilde{B_k}, B_k))$;

5: Repeat step 2 to step 5 until convergence

3.3.1 Hybrid Loss Function

The key idea of our hybrid loss include dual-cross loss and GAN loss. Dual-cross loss is to improve the performance of two generators by minimizing the square error between synthesized results and targets. The following $I, B, R, \widehat{B}, \widetilde{B}, \widehat{R}, \widetilde{R}$ are shown in Figure 2. That is,

$$\widehat{B} = G_B(I), \widehat{R} = G_R(I) \tag{1}$$

$$\ell_{\text{MSE}} = \|G_B(I) - B\|^2 + \|G_R(I) - R\|^2 \tag{2}$$

Furthermore, the dual generators swap their position to form a dual-cross structure. Hence, G_B receives the residual of I ÍC $\widehat{R}$ and G_R receives the residual of I ÍC $\widehat{B}$ as input respectively, and the corresponding loss function is defined as follows:

$$\widetilde{B} = G_B(I - \widehat{R}), \widetilde{R} = G_R(I - \widehat{B}) \tag{3}$$

$$\ell_{\text{MSE-cross}} = \|G_B(I - \widehat{R}) - B\|^2 + \|G_R(I - \widehat{B}) - R\|^2 \tag{4}$$

In general, the final $\ell_{dual-cross}$ is defined as:

$$\ell_{\text{dual-cross}} = \ell_{\text{MSE}} + \ell_{\text{MSE-cross}} \tag{5}$$

Hence, this $L_{dual-corss}$ allows the dual composed branches interact with each other. In other words, the synthesized background can help to infer realistic rain streaks, while the synthesized rain streaks in turn lead to realistic background. This makes each component learn the corresponding regression function well and then achieve satisfactory synthesized results.

In addition, The generators G_B, G_R try to minimize the whole objective function against the adversarial discriminator D that tries to maximize it. The discriminator D learns to distinguish real backgrounds from the synthesized ones. Since we end up with background synthesis, we only update the parameters of G_B during backward propagation period through the loss function of GAN:

$$\begin{aligned} \ell_{\text{GAN}} = log(D(B)) + log(1 - D(G_B(I))) \\ + log(1 - D(G_B(I - \widehat{R}))) \end{aligned} \tag{6}$$

In summary, the generators G_B, G_R and the discriminator D form a dual-cross generative adversarial network together, which enables the DDC-GAN to generate more sharper and realistic backgrounds and rain streaks. The whole model can be optimized by jointly solving the learning problem with the following two loss functions:

$$\min_{G_B, G_R} \max_{D} \ell_{\text{dual-cross}}(G_B, G_R) + \lambda \ell_{\text{GAN}}(G_B, D) \tag{7}$$

where λ balances the dual-cross loss and GAN loss, and we set it to 0.8 in our experiments.

3.3.2 Basic Architectures of Generator and Discriminator

We aim to train an end-to-end deep neural network for the rain removal task, but the original GAN [8] suffers from several training difficulties such as mode collapse and instable convergence, thus we have redesigned the basic structures of our two decomposed generators and single discriminator, which makes DDC-GAN focus on the synthesized qualities of results. The new structures of our generators and discriminator are shown in supplementary material.

4 Experiments

Table 1: Quantitative Evaluation

Baselines	Rain100L		Rain100H	
	PSNR	SSIM	PSNR	SSIM
ID	27.21	0.75	14.02	0.52
DSC	30.02	0.87	15.66	0.54
LP	32.02	0.91	14.26	0.42
SRCNN	34.41	0.94	20.02	0.67
Detail-Net	33.75	0.93	21.82	0.74
JORDER	36.02	0.96	23.45	0.75
SRGAN	35.07	0.94	25.45	0.87
DDC-CNN	34.95	0.94	25.11	0.85
DD-GAN	36.09	0.96	26.23	0.88
DDC-GAN	**37.21**	**0.98**	**27.13**	**0.90**

4.1 Datasets

To evaluate our approach, we compare DDC-GAN with state-of-the-art methods on both synthetic and real-world datasets: (1) Rain100L, which is the synthetic data set with synthetic rain streaks described as [27]; (2) Rain100H, which is the synthetic data set with five streak directions; (3) Real-world data set, which includes 20 real rain images with various types of rain streaks. Note that, all the training and testing data sets that we use are derived from [6] and [27], because they released their training and testing sets, as well as their source codes for synthesizing datasets. Here we express our heartfelt thanks to authors. For the training stage, the networks take images of 64*64 resolution as inputs. But in the testing stage, any resolution image size can be processed because our DDC-GAN is a fully convolutional network [20].

4.2 Baseline Methods and Ablation Studies

We compare our proposed method with state-of-the-art de-raining methods: image decomposition (ID) [15], layer priors (LP) [17], and discriminative sparse coding (DSC) [21]. Deep detail network [6] and JORDER [27] are both published in CVPR 2017, and authors have released their source code. SRCNN [14] and SRGAN [16] are implemented and trained by ourselves for rain removal task according to the methods provided by the authors. For the Quantitative Evaluation, two metrics Peak Signal-to-Noise Ratio (PSNR) [12] and Structure Similarity Index (SSIM) [26] are used as comparison criteria. For the Qualitative Evaluation. We not only show multiple subjective experimental results but also conduct a subjective experiment to demonstrate the effectiveness of our model in generating perceptual pleased results.

In order to analyse the efficacy of our decomposed network structure and dual-cross adversarial training mechanism, we also implement three ablated baselines for comparison:

1. *SRGAN*[16]. SRGAN is the naive application of Generator-B, which could be interpreted as an ablated DDC-GAN without decomposed dual-cross structure and optimization strategy, demonstrating the efficacy of decomposing and crossing procedure.

2. *DDC-CNN*. To further verify the effectiveness of adversarial optimization mechanism, we remove the GAN loss of DDC-GAN during training and propose DDC-CNN.

3. *DD-GAN*. To further verify the effectiveness of our proposed crossing procedure, we remove the cross operation of DDC-GAN during training and propose DD-GAN.

4.3 Quantitative Evaluation

Table 1 shows the results of different methods on Rain100L and Rain100H. From this table, we can observe that our DDC-GAN significantly outperforms other models in terms of both PSNR and SSIM. Note that our DDC-GAN has the ability to handle such heavy rainy cases, and achieves considerably better results. In addition, DDC-GAN gains over 2 dB in PSNR than other previous methods in heavy rain scene, such a large gain strongly demonstrates that the decomposed structure and training mechanism significantly boost the performance.

In addition, the complexity and time cost of different learning-based methods cost is an important issue. We further conducted a time cost comparison which was performed on a personal computer with Intel core i7-7700 central processing unit (CPU) at 3.60GHz

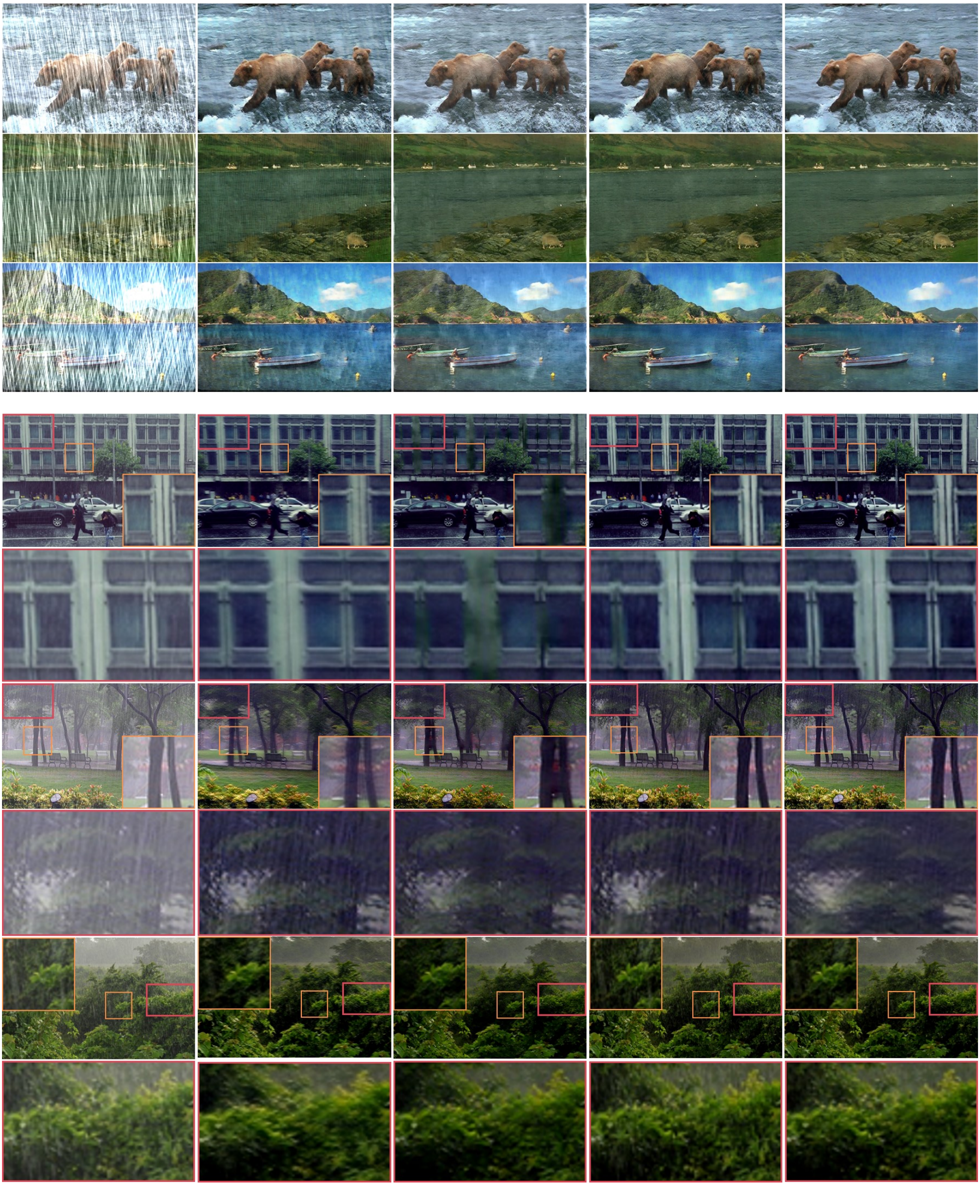

Figure 3: Results of different methods on synthetic (Top three rows) and real images (other rows). From left to right: rain image, Detail-Net, JORDER, SRGAN and DDC-GAN. Note that the image contents in the red boxes are enlarged and shown below the corresponding images.

and NVIDIA GeForce GTX 1080Ti GPU with 11GB memory. 5 synthetic rain pictures at resolution 500*500 are used for test, and the cost time results in GPU of DDC-GAN, Deep detail network [6], JORDER [27] are 6.27s, 6.51s, 7.69s respectively, which manifest that our DDC-GAN is considerably faster than the existing state-of-the-art learning-based methods.

4.4 Qualitative Evaluation

4.4.1 Evaluation on Synthetic and Real-world Test Data

Figure 3 shows the visual comparison of synthesized background images. As shown in the second and third column, method [6] leaves residual rain streaks in the background. This is because their method just uses signal-removal measures (i.e. filter) to extract pixel-wised features and then some rain streaks still exist in the low frequency part. JORDER proposed by [27] still generates smooth background due to the recurrent signal removal operation. In contrast, our DDC-GAN shown in the last column can remove rain streaks while still preserving details through our decomposed structure and training mechanism based on the signal composition idea. Furthermore, the pure SRGAN model is also inferior to our method.

Furthermore, we have conducted a subjective test to perceptually evaluate the de-rain results of our DDC-GAN and other methods. To build the subjective database, we choose 10 images randomly from Rain100L, Rain100H and real-world test data separately with a ratio of 3:4:3. And each image is de-rained by Detail-Net, JORDER, SRGAN, and DDC-GAN separately to generate 4 non-rain background images. Then 50 non-expert subjects are invited to participate in the test by showing one rainy image together with its four de-rained results by different methods. Every participant is instructed to vote for the best de-rained results based on the perceptual quality considering both rainy artifact and smoothness artifacts. Table 2 shows that DDC-GAN gets 316 votes from total 500 votes, which demonstrate its effectiveness in synthesizing more realistic and high-quality de-rained images. Finally, we specially conducted the user study on the real-world test data separated out from the overall combined subjective database (i.e. synthetic and real data set), the final results also showed that DDC-GAN has a strong ability to get more votes from total votes than other methods.

Figure 4: Synthesized rain streaks results of synthetic rainy image (top) and real-world rainy image (bottom).

Table 2: Subjective Experiment. Voting situation of different methods, the higher the better.

Baselines	Number of votes
Detail-Net	5
JORDER	111
SRGAN	68
DDC-GAN	316
Total	500

4.4.2 Rain Streaks Results and Application Extension: Dehazing and Denoising

Finally, we indicate that our DDC-GAN can also synthesize rain streaks image based on our decomposed network structure and the result corresponds to above $\widetilde{R}$ in Figure 2. Figure 4 shows the synthesized rain streaks results of synthetic rainy image and real-world rainy image. These results demonstrate that our proposed DDC-GAN also has the ability to infer realistic rain streaks, which lay the foundation for better rain removal results based on the idea of signal decomposition.

Finally, we mention that our DDC-GAN can be directly applied to other kinds of degraded images. The experimental results of image dehazing and denoising are illustrated in supplemental material. This test demonstrates that our proposed DDC-GAN is actually a general framework for image processing tasks.

5 Conclusions and Future Work

In this paper, we have introduced a Decomposed Dual-Cross Generative Adversarial Network (DDC-GAN) based on the idea of signal decomposition to address the single-image rain removal problem, especially in heavy rain. A decomposed network structure and a dual-cross adversarial training mechanism are proposed for perfect de-rained processing while still preserving texture details to the utmost extent. The two decomposed components promote each other and make progress together through the dual-cross adversarial training mechanism. Experiments demonstrate that our proposed DDC-GAN noticeably outperforms other state-of-the-art methods, including traditional and DNN-based frameworks, in terms of image perceptual and quantitative value. In the future, we can apply the proposed model to more challenging computer vision tasks, and then popularize the signal decomposition idea and dual-cross adversarial learning mechanism to more advanced and broader fields.

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