Semi-supervised CNN for Single Image Rain Removal

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Abstract. Single image rain removal is a typical inverse problem in computer vision. The deep learning technique has been verified to be effective to this task and achieved state-of-the-art performance. However, the method needs to pre-collect a large set of image pairs with/without rains for training, which not only makes the method laborsome to be practically implemented, but also tends to make the trained network bias to the training samples while less generalized to test samples with unseen rain types in training. To this issue, this paper firstly proposes a semi-supervised learning paradigm to this task. Different from traditional deep learning methods which use only supervised image pairs with/without rains, we put the real rainy images, without need of their clean ones, into the network training process as well. This is realized by elaborately formulating the residual between an input rainy image and its expected network output (clear image without rains) as a concise patch-wised Mixture of Gaussians distribution. The entire objective function for training network is thus the combination of the supervised data loss (least square loss between input clear image and the network output) and the unsupervised data loss. In this way, all such unsupervised rainy images, which is much easier to collect than supervised ones, can be rationally fed into the network training process, and thus both the short-of-training-sample and bias-to-supervised-sample issues can be evidently alleviated. Experiments implemented on synthetic and real data experiments verify the superiority of our model as compared to the state-of-the-arts.

Keywords: Semi-supervised learning, patch-based mixture of Gaussians, convolutional neural network, domain transfer

1 Introduction

Rain streaks and rain drops often occlude or blur the key information of the images captured outdoors. Thus the rain removal issue for an image or a video is useful and necessary, which can be served as an important pre-processing step for outdoor visual system. An effective rain removal technique can always help an image/video better deliver more detection or recognition results [1].

Current rain removal tasks can be mainly divided into two categories: video rain removal (VRR) and single image rain removal (SIRR). Compared with

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VRR, which could utilize the temporal correlation among consecutive frames, SIRR is generally much more difficult and challenging without the aid of much prior knowledge capable of being extracted from a single image. Since being firstly proposed by Kang et al. [1], the SIRR problem has been attracting much attention. Recently, deep learning methods [2,3,4,5,6,7] have been empirically substantiated to achieve state-of-the-art performance in SIRR by training an appropriate, carefully designed network to detect and remove the rain streaks simultaneously.

Albeit achieving good performance on the task, the current deep learning approach still exists some limitations. Firstly, for training data, since it is difficult to obtain clean/rainy image pairs from the real world data, the traditional skill is to add the "fake" rain synthesized by the Photoshop software\(^1\) to the clean image. The samples of such generated rainy images are shown in Figure 1.(b) and (c) (where the corresponding clean image is shown in Figure 1.(a)). Albeit being varied by the rain streaks direction and intensity, the generated rainy images still cannot sufficiently include wider range of rain streak types in real rainy images. For instance, in Figure 1.(d), the rain streaks have multiple directions in a single frame influenced by the wind; in Figure 1.(e), the rain streaks have multiple layers because of their different distances to the camera; in Figure 1.(f), the rain streaks produce the effect of aggregation which is similar to fog or mist. It is therefore very easy to exist bias between generated training data and real world rainy images, naturally leading to the issue that the network trained on the generated training data not capable of being finely generalized to the real world rainy images.

\(^1\) https://www.photoshopessentials.com/photo-effects/rain/
Meanwhile, one of the main problems for deep learning methods lies on the preliminary conditions that they generally need sufficiently large number of supervised samples (images with/without rains), which are generally time-consuming and laborsome to collect even when we manually generate them to possibly covering wider range of rain types. Simultaneously, one generally can easily attain large amount of practical unsupervised samples, i.e., rainy images, while without their corresponding clean ones. How to rationally feed these cheap samples into the network training is not only meaningful and necessary for the investigated task, but also possibly inevitable in the next generation of deep learning to fully prompt its capability on unsupervised data for general image restoration tasks.

Except for deep learning methods, there also exist multiple model-based SIRR methods, like discriminative sparse coding [8], layer priors model [9], joint bi-layer optimization method [10]. These methods carefully combine the prior knowledge of rain streaks into their models to extract rains from an image. However, most of these model-based methods suffer from the cost of time and are not applicable for real applications, and also less performed than deep learning techniques.

To alleviate the aforementioned issues of deep learning in the SIRR task, we propose a new semi-supervised SIRR method attempting to effectively feed unsupervised samples into the network training. Dominantly different from previous deep learning methods by only using supervised image pairs as inputs, our method is capable of fully utilizing unsupervised practical rainy images in training in a mathematically sound manner. Specifically, our model allows both the supervised “generated” data and the unsupervised “real” data being fed into the network, and the network parameters can be optimized by the combination of least square residuals on supervised samples measured between network output images and their clean ones, and patch-wised MoG (P-MoG) losses on unsupervised ones measured between network output images and the original rainy ones. The latter is designed based on the fact that the deviation between a rainy image and its expected output clean image can be well formulated as a P-MoG distributions [11]. In this manner, both supervised and unsupervised samples can be rationally employed in our method for network training.

In summary, the main contributions of the proposed method are:

– We firstly construct a semi-supervised deep learning framework for the SIRR task. Different from the previous deep learning SIRR methods, our model can fully take use of the unsupervised rainy images, without need of the corresponding clean ones, easily being collected in practice. Such unsupervised samples not only help evidently reduce the time and labor costs of pre-collecting image pairs with/without rains for network parameter updating, but also alleviate the over-fitting issue of the CNN on limited rain types covered by supervised training samples through compensating those unsupervised ones containing more general and practical rain characteristics.

– Our model provides a general way for combinationally utilizing supervised and unsupervised knowledge for image restoration tasks. For supervised one,
the traditional least square loss between network output images and their

We design an EM algorithm together with a gradient descent strategy to

The rest of this paper is organized as follows. In Section 2 we detailedly review

2 Related work

2.1 Single image rain removal methods

The problem of SIRR was firstly proposed by Kang et al. [1]. They detected the

Li et al.’s [9] incorporated patch-based Gaussian mixture model prior information for image background and rain layer, and trained the model parameters by pre-collected clean and rainy images. Similarly, Zhang et al. [13] learned a set of generic sparsity-based and low-rank representation-based convolutional filters to represent background and rain streaks, respectively. Gu et al. [14] combined analysis sparse representation to represent image large-scale structures and synthesis sparse representation to represent image fine-scale textures, including the directional prior and the non-negativeness prior in their JCAS model. More recently, Zhu et al. [10] proposed a joint optimization process that alternates between removing rain-streak details from background layer and removing non-streak details from rain layer. Their model is largely aided by the rain priors, which are narrow directions and self-similarity of rain patches, and the background prior, which is centralized sparse representation. Chang et al. [15] transformed an input rainy image into a domain where the line pattern appearance has an extremely distinct low-rank structure, and proposed a model with compositional directional total variational and low-rank prior for the image, to deal
Deep learning has been substantiated to be effective in many computer vision tasks [16,17,18,19,20], so does in the SIRR task. Fu et al. firstly introduced deep learning technique into this area in [2]. They trained a three hidden layers convolutional neural network (CNN) on the high frequency detail domain of the image. Later, Fu et al. [3] further ameliorated the CNN by introducing deeper hidden layers, batch normalization and negative residual mapping structure, and achieved better effect. To better deal with the scenario of heavy rain images (where individual streaks are hardly seen, and thus visually similar to mist or fog), Yang et al. [4] exploited a contextualized dilated network with a binary map. In their model, a continuous process of rain streak detection, estimation and removal are predicted in a sequential order. Zhang et al. [6] applied the mechanism of generative adversarial network (GAN [21,22]) and introduced a perceptual loss function for the consideration of rain removal problem. Afterwards, Li et al. [5] used a scale-aware multi-stage convolutional neural network, mainly aiming at solving the condition with heavy rain, where rain streaks are of various sizes and directions.

2.2 Video rain removal methods

For literature comprehensiveness, we simply list several representative state-of-the-art video rain removal methods. Since the extra inter-frame information is extremely helpful, these methods realized relatively better reconstruction effect than SIRR methods. Earlier video derain methods [23,24,25,26] designed many useful techniques to detect potential rain streaks based on their physical characteristics and removed these detected rains by image reconstruction algorithms. In recently years, low-rankness [27,28], total variation [29], stochastic distribution priors [11] have been applied to the model and these work achieved satisfying results in video rain removal problem.

Since the SIRR problem is more difficult in real world with less information provided other than a rainy image, to design an effective SIRR regime is also more challenging beyond VRR ones.

3 Semi-supervised model for SIRR

We show the framework of our model which includes the training data and the network structure in Figure 2. As introduced aforementioned, our model is capable of feeding both supervised generated rainy data and unsupervised real rainy data into the network training process.

3.1 Model formulation

Unsupervised sample learning. As shown in Figure 1.(d)(e)(f), the real world rains always show relatively complex patterns and representations. However, because of the technical defects, these data whose label (i.e., the corresponding clean images) are unavailable which is possibly the main reason that
Fig. 2. The framework of the proposed method. The upper panel shows the supervised learning term, which is to minimize the difference of network output and the corresponding clean image using a Frobenius norm. The lower panel shows the unsupervised learning term, which is to minimize the negative log-likelihood of real rain streaks distribution, which is assumed as a P-MoG distribution. The network structure and parameters are shared in both parts.

they are not considered in previous SIRR deep learning techniques. Inspired by [11], we assume the set of rain patches $\mathcal{R}$ in real world rainy images as a patch-wised mixture of Gaussians (P-MoG) distribution, which means that the differences between the input real rain images and corresponding network output clean images follow a P-MoG distribution as shown in lower panel of Figure 2. That is,

$$\mathcal{R} \sim \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathcal{R} | \mu_k, \Sigma_k),$$  \hspace{1cm} (1)

where $\pi_k, \mu_k, \Sigma_k$ denote the mixture coefficients, Gaussian distribution mean and covariance parameters. It has been verified that P-MoG is a proper representation for rain distributions [11], and thus it is suitable to be utilized to describe the rain streaks to-be-extracted from the input rainy image. Thus the log likelihood function imposed on these unsupervised samples can be written as:

$$L_{unsupervised}(\mathcal{R}; \Pi, \Sigma) = \sum_{n=1}^{N} \log \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathcal{R}_n | 0, \Sigma_k),$$  \hspace{1cm} (2)

where $\Pi = \pi_1, \ldots, \pi_K$, $\Sigma = \Sigma_1, \ldots, \Sigma_K$, $K$ is the number of mixture components, $\mathcal{R} = \mathcal{R}_1, \ldots, \mathcal{R}_N$, $n = 1, \ldots, N$, and $N$ is the number of patches. Each $\mathcal{R}_i$ represents the patch value of the supposed rain layer to be separated. Note that the means of Gaussian distributions are manually set to be zero, and this doesn’t affect the results in our experiments.
By utilizing the above encoding manner, we can also construct an objective function for unsupervised rainy images, which can be further used to fine-tune the network parameters through back-propagating its gradients to the network layers.

**Supervised sample learning.** Meanwhile, we follow the network structure and negative residual mapping skill of DerainNet [3] (a deep detail convolutional neural network) to formulate the loss function on supervised samples. The input of the CNN which is denoted by \( f_w(\cdot) \) (here \( w \) represents the network parameters) representing the high-frequency detail layer of the rainy image and the output is the negative rain layer. Thus the expected rain-removed result \( g_w(x_i) \) of a rainy input \( x_i \) is shown as:

\[
g_w(x_i) = f_w(x_{i,detail}) + x_i, \tag{3}
\]

where \( x_i, i = 1, \ldots, N \) represents the pixels of the rainy image. The classical loss function of CNN is to minimize the Euclidean distance between the desired output \( g_w(x_i) \) and the ground truth label \( y_i \). That is, the loss function imposed on the supervised samples is with the following least square form:

\[
\mathcal{L}_{\text{supervised}} = \sum_{i=1}^{N} ||g_w(x_i) - y_i||^2_F, \tag{4}
\]

**Semi-supervised SIRR model.** By combining Eq. (2) and (4), the entire objective function to train the network can be formulated as follows:

\[
\mathcal{L}(w, \Pi, \Sigma) = \sum_{i=1}^{N_1} ||g_w(x_i) - y_i||^2_F - \lambda \sum_{n=1}^{N_2} \log \sum_{k=1}^{K} \pi_k \mathcal{N}(\tilde{x}_n - g_w(\tilde{x})_n|0, \Sigma_k), \tag{5}
\]

where \( x_i, y_i, i = 1, \ldots, N_1 \) represent corresponding rain and rain-free pixels pairs of the supervised data, and \( \tilde{x}_n, n = 1, \ldots, N_2 \) represent the real rain patches in the unsupervised data without ground truth labels. In the second term of Eq. (5), the unsupervised data can be fed into the same network with that imposed on the supervised data, and the term \( \tilde{x}_n - g_w(\tilde{x})_n \) is the supposed rain patches calculated directly on the input rainy image, which is equivalent to \( \mathcal{R}_n \) as defined in Eq. (2). \( \lambda \) is the trade-off parameter, which balances the functions of supervised and unsupervised learning model. Note that when \( \lambda \) equals to 0, our model degenerates to the conventional supervised deep learning model [3].

By using such objective setting, the network can be trained not only on the well annotated supervised data, but also on the purely unsupervised inputs by fully encoding the prior structures underlying rain streak distributions. As compared with the traditional deep learning techniques implemented on only supervised samples, the better generalization effect of the network is expected due to the fact that it facilitates a rational transferring effect from the supervised samples to unsupervised types of rains.
3.2 The EM algorithm

Since the loss function in Eq. (5) is intractable, we use the Expectation Maximization algorithm \[30\] to iteratively solve the model. In E step, the posterior distribution which represents the responsibility of certain mixture component is calculated. In M step, the P-MoG and the convolutional neural network parameters are updated.

**E step**: Introduce a latent variable $z_{nk}$ where $z_{nk} \in \{0, 1\}$ and $\sum_{k=1}^{K} z_{nk} = 1$, indicating the assignment of noise term $(\tilde{x}_n - g_w(\tilde{x})_n)$ to a certain component of the mixture model. According to the Bayes’ theorem, the posterior responsibility of component $k$ for generating the noise is given by:

$$
\gamma_{nk} = \frac{\pi_k \mathcal{N}(\tilde{x}_n - g_w(\tilde{x})_n | 0, \Sigma_k)}{\sum_k \pi_k \mathcal{N}(\tilde{x}_n - g_w(\tilde{x})_n | 0, \Sigma_k)}.
$$

(6)

**M step**: After the E step, the loss function in Eq. (5) is unfolded into a differential one with respect to P-MoG and convolutional neural network parameters, shown as:

$$
\min_{w, \Pi, \Sigma} \lambda \sum_{n=1}^{N_2} \sum_{k=1}^{K} \gamma_{nk} \left( \frac{1}{2} (x_n - g_w(\tilde{x})_n)^T \Sigma_k^{-1} (x_n - g_w(\tilde{x})_n) \right)
$$

$$
+ \frac{1}{2} \log | \Sigma_k | - \log \pi_k + \sum_{i=1}^{N_1} ||g_w(x_i) - y_i||_F^2.
$$

(7)

The closed-form solution of mixture coefficients and Gaussian covariance parameters are \[30\]:

$$
N_k = \sum_{n=1}^{N} \gamma_{nk}, \quad \pi_k = \frac{N_k}{N},
$$

(8)

$$
\Sigma_k = \frac{1}{N_k} \sum_{n=1}^{N} \gamma_{nk} (\tilde{x}_n - g(\tilde{x})_n)(\tilde{x}_n - g(\tilde{x})_n)^T, \quad k = 1, \ldots K.
$$

(9)

Then we can employ the off-the-shelf gradient propagation methods to optimize the objective function as defined in Eq. (7) and updates the network parameters $w$. The details will be introduced in the next subsection. Overall, in each EM iteration, we optimize the posterior probabilities, P-MoG parameters and network parameters in an iterative manner.

3.3 Network training

Since the concentration of our paper is not to design a new neural network structure while to better represent the effect of our unsupervised term, we choose to follow the framework of the supervised learning part from the state-of-the-art DerainNet work \[3\] and use their network structure as pipeline of our method.

As can be seen in Eq. (7), the network parameters $w$ can be updated by back propagating the gradients of the following objective function, which is the combination of Eq. (3) and (7):
Fig. 3. The framework of the proposed semi-supervised model. Both supervised and unsupervised data are decomposed and the high-frequency detail layers are supposed to be the input of the network. The network which is framed by dotted line has 26 blocks. Each block has the operation of convolutional filtering, batch normalization [31] and ReLU activation function. The outputs of both supervised and unsupervised data are negative residuals which are the opposites of the rain layer. The deraining result is obtained by adding the network output and rainy image together.

\[
\min_{w, H, \Sigma} \lambda \sum_{n=1}^{N_2} \sum_{k=1}^{K} \gamma_{nk} \left( \frac{1}{2} f_w(\tilde{x}_{n,detail})^T \Sigma_k^{-1} f_w(\tilde{x}_{n,detail}) \right) + \frac{1}{2} \log |\Sigma_k| - \log \pi_k + \sum_{i=1}^{N_1} ||f_w(x_{i,detail}) + x_i - y_i||_F^2.
\]

Here, \( f(\cdot) \) represents the residual net [20] and \( w \) denote the trainable network parameters. The detail layer is obtained by low-pass filtering [32]. Note that we can easily calculate the gradients of both terms in the above objective since both of them are with quadratic forms of the network output \( f_w(x) \). The gradient so calculated can thus be easily fed back to the network to gradually ameliorate its parameters \( w \). The network flowchart is shown in Figure 3. We readily utilize the off-the-shelf gradient-based optimization algorithm Adam [33] for network parameter training on the objective function 7 imposed on both supervised and unsupervised training samples.

4 Experiments

In this section, we evaluate our methods both on synthetic rainy data and real world rainy data. The compared methods include the state-of-the-art discriminative sparse coding based method (DSC) [8], layer priors based method (LP) [9], CNN method [3], joint bi-layer optimization (JBO) [10] and multi-task deep learning method (JORDER) [4]. These methods include data-driven deep learning methods and model-driven methods. Our method to a certain extent can be viewed as the combination of data-driven and model-driven techniques.
4.1 Implementation details

For supervised training data, we use one million 64×64 rainy/clean image patch pairs, which is in similar way with the baseline CNN method [3]. The clean images are collected from the the UCID dataset [34], the BSD dataset [35] and Google image search. For unsupervised training data, we collect the real world rainy images from the dataset provided by [4,11,6]. We randomly cropped one million image patches from these images to constitute the unsupervised samples.

We design the number of P-MoG components as 3. For the trade-off parameter \( \lambda \), we simply set it as 5 throughout all our experiments. The network structures and related parameters are directly inherited from the baseline method [3].

4.2 Experiments on synthetic images

In this subsection, we evaluate the rain removal effect of our method with synthetic data by both visual quality and performance metric. We use the skill of
Table 1. Mean PSNR comparison of two groups of data on synthetic rainy images.

| Dataset | Input | DSC[8] | LP[9] | JORDER[4] | CNN[3] | JBO[10] | Ours |
|---------|-------|--------|-------|-----------|--------|---------|------|
| Dense   | 14.69 | 15.60  | 15.56 | 14.68     | 16.07  | 14.87   | 18.01|
| Sparse  | 25.03 | 26.09  | 26.86 | 25.90     | 28.01  | 25.24   | 28.32|

[11] to synthesize the rainy image, by adding the captured pure rain streaks images under black background to the clean images, which is randomly selected from the Berkeley Segmentation Dataset [36].

Considering the complexity and multiformity of the rain streaks, we compare our methods with others under two different scenarios: sparse rain streaks and dense rain streaks. Figure 4 shows an example of synthetic data with sparse rain streaks. The added rain streaks are sparse but with multiple lengths and layers, in consideration of the different distance to the camera. As shown in Figure 4, the DSC method [8] and JBO method [10] fail to remove the main component of the rain streaks. The LP method [9] tends to blur the visual effect of the image and destroy the texture and edge information. The two deep learning methods CNN [3] and JORDER [4] have better rain removal effect, but rain streaks still clearly exist in their results. Comparatively, our method could best remove the sparse rain streaks and keep the background information.

We also design the experiments with dense rain streaks scenario. In real world, the dense rain streaks have the effect of aggregation, even blurring the image similar to the conditions of fog or mist when the rain is heavy. In Figure 5, the added rain is heavy, with not only the long rain streaks, but also the brought blurring effect damaging the image visual quality. As shown in Figure 5, the results of DSC [8], JORDER [4] and JBO [10] still have obvious rain streaks, while LP [9] still over-smoothed the image. Compared with the baseline CNN method [3], our method have better reconstruction results because our semi-supervised is trained partly with unsupervised real rain data.

Since the ground truth is known for the synthetic problem, we use the most extensive performance metric Peak Signal-to-Noise Ratio (PSNR) for a quantitative evaluation. As is evident in Table 1, we have the best PSNR in both two groups of data with different scenarios, in agreement with the visual effect in Figure 4 and 5. Subjected to limited length of the paper, more rain removal results of our method in compared with the previous methods are shown in supplementary material.

4.3 Experiments on real images

The most direct and efficient way to evaluate a single image rain removal method is to see its visual effect of reconstruction results on the real world rainy images. We use the testing data selected from the Google search. To best represent the diversity of the real rain scenarios, we intentionally select images with different types of rain streaks. In Figure 6 and 7, the rain streaks are sparse but obvious. Both samples represent our method can remove the most rain streaks and best keep the visual quality. Also, we conduct the real experiments with dense rain
streaks. As shown in Figure 8, the reconstruction result of our method is mostly clear, while the compared methods either bring blurring artifact or keep rain streaks in their results.

4.4 Discussion on the function of unsupervised data

The main difference of the proposed method from the other deep learning SIRR methods is the involvement of the real world rainy images whose ground truth
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(a) Input  (b) LP [9]  (c) CNN [3]
(d) JORDER [4]  (e) JBO[10]  (f) Ours

Fig. 8. Real rain streaks removal experiments with dense rain.

label (corresponding rain-free image or ground-truth rains) are unavailable. One main motivation for this investigation is that the manually generated rain shapes usually differ from real ones collected in practice. According to several SIRR methods in the framework of deep learning [2,3], clean images are used to generate rainy images by Photoshop software. Although each clean image is supposed to generate several different type of rainy image, as shown in upper panel of Figure 1, the difference of scale, illuminance and distance to the camera of the real rain streaks are hardly sufficiently considered, thus yielding significant gap between the generated rainy images for training and the real rainy images for testing.

In the proposed method, the involvement of the unsupervised real rainy data well alleviates this problem. As shown in Figure 9, we use the same Photoshopped data with [3] as the training data. To verify the superiority of our model on this point, we use the real rains captured by in the totally black background [11] covered on the clean images as the validation data, to most degree approaching the real rain streaks. Therefore the training rain and validation rain lie in distinct domains. We found that our model shows better capability to overcome the gap and transfer from the generated rain data to real rain data, as shown in Column 3-5 of Figure 9. Although our semi-supervised model not extremely finely fit the training effect of the generated data (as shown in Column 1 of Figure 9), Column 2 of Figure 9 reflects our model have better real rain removal effect.

5 Conclusions

In this paper, we firstly tackle the SIRR problem in a semi-supervised manner. We train a CNN on both supervised and unsupervised rainy images. In this
Fig. 9. The PSNR trend graph of the training data and validation data during training process. The solid line represents training process and the dotted line represents validation process. The red, green, blue lines represent the trade-off parameter $\lambda$ in Eq. (5) equals to 0 (equivalent to supervised learning), 0.2 and 1, respectively. The three rows use five hundred, five thousand and ten thousand image patches as the training data from top to bottom.

manner, our method especially alleviates the hard-to-collect-training-sample and overfitting-to-training-sample issues existed in conventional deep learning methods designed for this task. The experiments implemented on synthetic and real images substantiate the effectiveness of the proposed method.

For future work, we consider to adopt the semi-supervised learning insight into other inverse problems. We wish to apply the human prior knowledge into the training process of deep learning framework, more sufficiently realizing the combination of data-driven and model-driven methods. The ultimate goal is to take advantage of both data-based deep learning method, which is learning knowledge from available data and shortening the testing time to fulfill the online task requirement, and model-based method, to put the network training into a more explainable direction.

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