INTEGRATING DEGRADATION LEARNING INTO IMAGE RESTORATION

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ABSTRACT

Existing image restoration methods usually assume specific degradation model, e.g., linear combination of clean image and degradation map in image denoising and deraining. Benefiting from the power of deep learning, a restoration mapping can be learned from degraded image to latent clean image. In this paper, we propose to integrate degradation learning into image restoration (IDLIR), where degradation model can be learned from training samples. In particular, IDLIR is an iterative restoration framework, where latent clean image and degradation map can be extracted from current residual degraded image, and are then fused by a degradation network to reconstruct degraded image. Then the residual degradation image can be updated by computing the difference between input and reconstructed degraded images. By taking denoising and deraining as examples, IDLIR is compared with state-of-the-art methods on several benchmark datasets. IDLIR performs better than state-of-the-art methods quantitatively and qualitatively.

Index Terms— Image restoration, image denoising, image deraining

1. INTRODUCTION

Image restoration, aiming at recovering latent clean image from input degraded image, is a fundamental and active research field, drawing much research attention in the deep learning era. Based on deep learning, a restoration map can be learned from input degraded image to latent clean image. Image denoising and image deraining are two representative tasks, and a variety of restoration methods have been developed, e.g., MPRNet [1], PReNet [2] , RESCAN [3] and MSPFN [4] for image deraining, and HINet [5], DnCNN [6], SADNet [7] and DANet+ [8] for image denoising.

Benefiting the power of deep learning, these restoration methods usually focus on designing the mapping network, while neglecting the degradation model. Such as DnCNN for denoising and PReNet for deraining, residual learning is suggested to first predict degradation map, which is then subtracted from degraded image to obtain latent clean image. In these methods, a linear degradation model is actually assumed. However, degradation model in real cases is much more complex than linear model, e.g., noises and rain streaks are actually not linear and may be dependent on latent clean image. We suggest that the degradation model should be learned as well as image restoration procedure.

In this paper, we propose to integrate degradation learning into image restoration (IDLIR), where degradation network and restoration network can be jointly learned from training samples. As shown in Fig. 1, IDLIR is an iterative framework, where latent clean image and degradation map can be extracted from current residual degraded image, and are then fused to form current degraded image by introducing a degradation network $\mathcal{F}$. In particular, residual degraded image ΔZ^n for iteration n can be obtained by calculating the difference between reconstructed degraded image Z^{n-1} and input degraded image Z. Then from ΔZ^n, residual components of latent image ΔX^n and degradation map ΔY^n can be extracted using restoration model $\mathcal{H}$, and can be added to latent image X^{n+1} and Y^{n+1} for refining restoration results. By introducing degradation network $\mathcal{F}$, degradation model can be accordingly learned instead of naive linear model.

IDLIR is applied to image denoising and image deraining. Extensive experiments are conducted to verify the effectiveness of IDLIR, where IDLIR can obtain notable performance gains than state-of-the-art methods. IDLIR also performs more favorably in terms of restoration visual quality. The contributions of this work can be summarized as:

- We propose a joint learning framework of degradation and restoration, where degradation model can be learned instead of commonly adopted linear degradation model.
- By integrating degradation learning into image restoration, IDLIR model is developed for image denoising and image deraining.
- Extensive experiments on image deraining and denoising are conducted to verify the effectiveness of IDLIR.

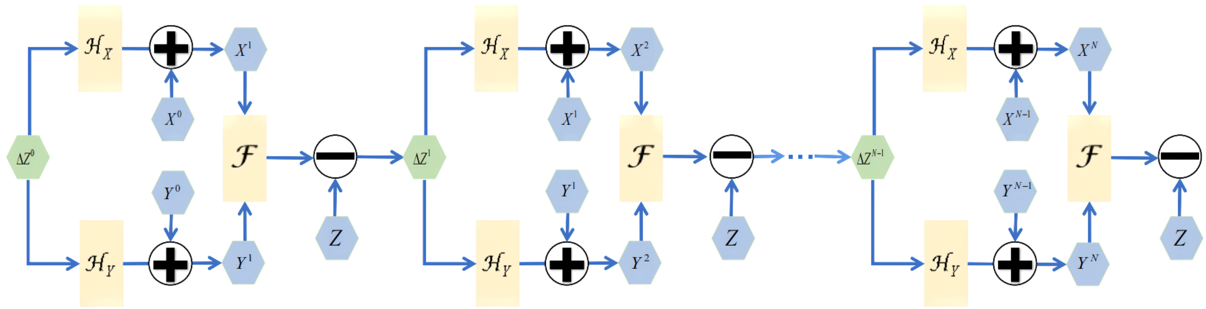

Fig. 1. Framework of IDLIR, where latent image X^n and degradation map Y^n can be refined by extracting information from residual degraded image ΔZ^{n-1} via restoration network $\mathcal{H}_X$ and $\mathcal{H}_Y$, respectively. The reconstructed degraded image Z^n can be obtained by fusing X^n and Y^n via a learned degradation network $\mathcal{F}$.

2. RELATED WORK

In this section, we briefly review restoration methods including traditional methods and deep learning-based methods.

2.1. Traditional Restoration Methods

The traditional method of rain removal for a single image is mainly based on a prior modeling of the rain layer and background, separating the rain layer and the non-rain layer. At the same time, it is necessary to design a reasonable loss function and solve the problem by optimizing the objective function. Kang et al. [9] obtained high and low frequency information by decomposing the image and decomposing the information of the high frequency layer into rain and no rain on the basis of dictionary learning and sparse representation, and then combined with the low frequency information to restore a clear rain-free image. Luo et al. [10] also adopted the strategy of separating the rain layer from the non-rain layer. The difference is that a mutually exclusive learning dictionary is added when discriminating sparse representations. In [11], Wang used the color, direction and structure of raindrops to determine whether it is a dynamic component, so as to detect rain streaks for separation. In its follow-up research [12], raindrops are regarded as additive noise, the global rain layer parameters are estimated with local linear model parameters, and the rain layer is stripped to achieve clean image.

2.2. Deep Learning-based Methods

Fu et al. proposed a deep detail network in [13], which makes full use of high-frequency information to extract rain layer features and non-rain layer features. Its advantage is that it can process larger rain streaks. Zhang et al. [14] used the density of rain streaks as the starting point and proposed a dense sensing method to remove rain. Jiang et al. [4] achieved the fusion of information at different scales through multi-scale feature extraction, so as to achieve the purpose of rain removal. It is worth mentioning that in the follow-up research, there has been a rain removal technology that combines physical models and deep learning technologies. The representative ones are [15] and [16] respectively, where different physical models are suggested to guiding the restoration of rainy images. The development of generative confrontation network has further promoted the development of rain removal methods. Zhang et al. [17] can show better visual effects without more visual attributes through the confrontation generative network, but it will produce visual artifacts. When restoring images, a complex balance needs to be struck between spatial details and contextual information, and a co-designed MPRNet is proposed in [1],which is mainly a multi-stage architecture that gradually learns the restoration function of degraded inputs, this balance can be achieved.

3. PROPOSED METHOD

In this section, we first introduce the framework of integrating degradation learning into image restoration, then present the network architecture, and finally give learning objective for network tranining.

3.1. Integrating Degradation Learning into Image Restoration

For image restoration tasks, e.g., denoising and deraining, liner degradation model is usually assumed

$$Z = X + Y, \tag{1}$$

where Z is the degraded image, Y is the degradation map (i.e., noises for denoising, rain streaks for deraining), and X is latent clean image. Thanks to the power of deep learning, state-of-the-art restoration networks have been developed by learning a mapping from degraded image to latent clean image, e.g., RESCAN [3] , PReNet [2] , MSPFN [4] for deraining and SADNet [7] and DANet+ [8] for denoising. In these methods, residual learning [18] is usually adopted to predict degradation map, which is then subtracted from degraded image for generating latent clean image. However, degradation model is usually more complicated than the linear model in real cases, e.g., noises are usually not linear and dependent on signal, making existing methods remains some leeway for further improving restoration performance.

In this work, we propose to integrate degradation learning into image restoration (IDLIR) procedure, in which the degradaion model is learned instead of naive linear combination of degradation map and clean image. IDLIR is an iterative framework, whose steps at time n are summarized as

$$\begin{aligned} \Delta Z_n &= Z - Z_{n-1}, \\ (\Delta X_n, \Delta Y_n) &= \mathcal{H}(\Delta Z_n), \\ X_n &= X_{n-1} + \Delta X_n, \\ Y_n &= Y_{n-1} + \Delta Y_n, \\ Z_n &= \mathcal{F}(X_n, Y_n), \end{aligned} \tag{2}$$

where $\mathcal{H}$ is restoration network and $\mathcal{F}$ is the degradation network for reconstructing degraded image. For current residual degraded image ΔZ_n, residual components ΔX_n and ΔY_n can be recovered, and then degradation map Y_n and latent clean image X_n can be refined by adding these residual components. In IDLIR, degradation network $\mathcal{F}$ can be accordingly learned to reconstruct degraded image Z_n, which is expected to be closer to input degraded image Z, i.e., $\Delta Z_n \to 0$ with $n \to +\infty$. As for the initialization, $Z_0 = 0$, $X_0 = 0$ and $Y_0 = 0$

3.2. Network Architecture

IDLIR consists of two networks, i.e., restoration Network $\mathcal{H}$ and degradation network $\mathcal{F}$. IDLIR is an iterative framework, and the networks $\mathcal{H}$ and $\mathcal{F}$ share parameters across different stages. In the following, we present network architecture of $\mathcal{H}$ and $\mathcal{F}$, and their souce code has been available at Github `https://github.com/tjucvmmy/IDILR/tree/main/IDLIR`.

Restoration Network $\mathcal{H}$**:** Given residual degraded image ΔZ, $\mathcal{H}$ aims to recover residual components ΔX and ΔY. In this work, we propose to respectively estimate ΔX and ΔY, i.e., $\mathcal{H}$ consists of two individual networks $\mathcal{H}_X$ and $\mathcal{H}_Y$.

X-Net $\mathcal{H}_X$**:** To better exploit the multi-scale information for predicting latent clean image, we follow [4] to adopt a multi-scale network to act as network $\mathcal{H}_X$. Due to limited space, architecture details are not given in this paper, and can be found in the source code.

Y-Net $\mathcal{H}_Y$**:** Since degradation map is usually simpler than latent image, we suggest to employ ResNet [18, 22] with 4 residual blocks to serve as $\mathcal{H}_Y$.

Degradation Network $\mathcal{F}$**:** To reconstruct degraded image Z_n, we need to fuse estimated degradation map Y_n and latent clean image X_n. We adopt a multi-scale fusion network to reconstruct Z_n, whose architecture details can be found in source code.

3.3. Learning Objective

To train IDLIR for image deraining and image denoising, we can impose supervision on both latent image X^N and reconstructed degraded image Z^N after N iterations,

$$\mathcal{L}_1 = \ell(X^{gt}, X^N) + \ell(Z, Z^N), \tag{3}$$

where X^{gt} is ground-truth clean image. Furthermore, we experimentally found that it can achieve better results by only imposing supervision on the latent clean image,

$$\mathcal{L}_2 = \ell(X^{gt}, X^N), \tag{4}$$

where degradation model can also be implicitly learned by degradation network $\mathcal{F}$. As for the choice of loss ℓ, it can be either mean square error (MSE) or negative SSIM [23], and in this work we suggest to adopt negative SSIM for training the final IDLIR.

4. EXPERIMENTAL RESULTS

This section qualitatively and quantitatively evaluates the effectiveness of IDLIR on image deraining and image denoising on several benchmark datasets. Ablation studies have also been conducted to analyze IDLIR.

4.1. Datasets and Implementation

Datasets. *Image Deraning*: We take several mixed rainy datasets as the training set by following [4]. The mixed dataset comes from [14, 19], including 13,712 training image pairs. As for testing sets, we adopt Test100 [17], Rain100H [19], Rain100L [19], Test1200 [14] and Test2800 [13] to evaluate the competing deraining methods. *Image Denoising*: We adopt 320 high-resolution images on the SSID [24] dataset to train our model, and then evaluation is conducted on 1,280 validation patches from the SIDD dataset [24] and DND [25] dateset.

Implementation Details. The IDLIR models for image deraning and denoising share the same training strategy. The networks are trained on 100×100 patches with a batch size of 7 for 50 epochs. The ADAM [26] algorithm is adopted to train the models with an initial learning rate 4×10^{-4}. When reaching 10, 20, 30 and 40 epochs, the learning rate is decayed by multiplying 0.5.

4.2. Evaluation with Image Deraining

For the task of single image deraining, our IDLIR is compared with DerainNet [13], SEMI [20], DIDMDN [14], URML [21], RESCAN [3], PReNet [2] and MSPFN [4].The restoration performance is evaluated using PSNR and SSIM. As reported in Table 1, our IDLIR is superior to all the competing methods on the five testing sets. Due to the introduction of learning degradation model, our IDLIR can achieve notable

Table 1. Evaluation on image deraining task. These models are trained on mixed training sets, and are then evaluated on five testing sets.

Methods	Test100 [17]		Rain100H [19]		Rain100L [19]		Test2800 [13]		Test1200 [14]	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
DerainNet [13]	22.77	0.810	14.92	0.592	27.03	0.884	24.31	0.861	23.38	0.835
SEMI [20]	22.35	0.788	16.56	0.486	25.03	0.842	24.43	0.782	26.05	0.822
DIDMDN [14]	22.56	0.818	17.35	0.524	25.23	0.741	28.13	0.867	29.65	0.901
UMRL [21]	24.41	0.829	26.01	0.832	19.18	0.923	29.97	0.905	30.55	0.910
RESCAN [3]	25.00	0.835	26.36	0.786	29.80	0.881	31.29	0.904	30.51	0.882
PreNet [2]	24.81	0.851	26.77	0.858	32.44	0.950	31.75	0.916	31.36	0.911
MSPFN [4]	27.50	0.876	28.66	0.860	32.40	0.933	32.82	0.930	**32.39**	0.916
IDLIR	**28.33**	**0.894**	**29.33**	**0.886**	**35.72**	**0.965**	**32.93**	**0.936**	32.06	**0.917**

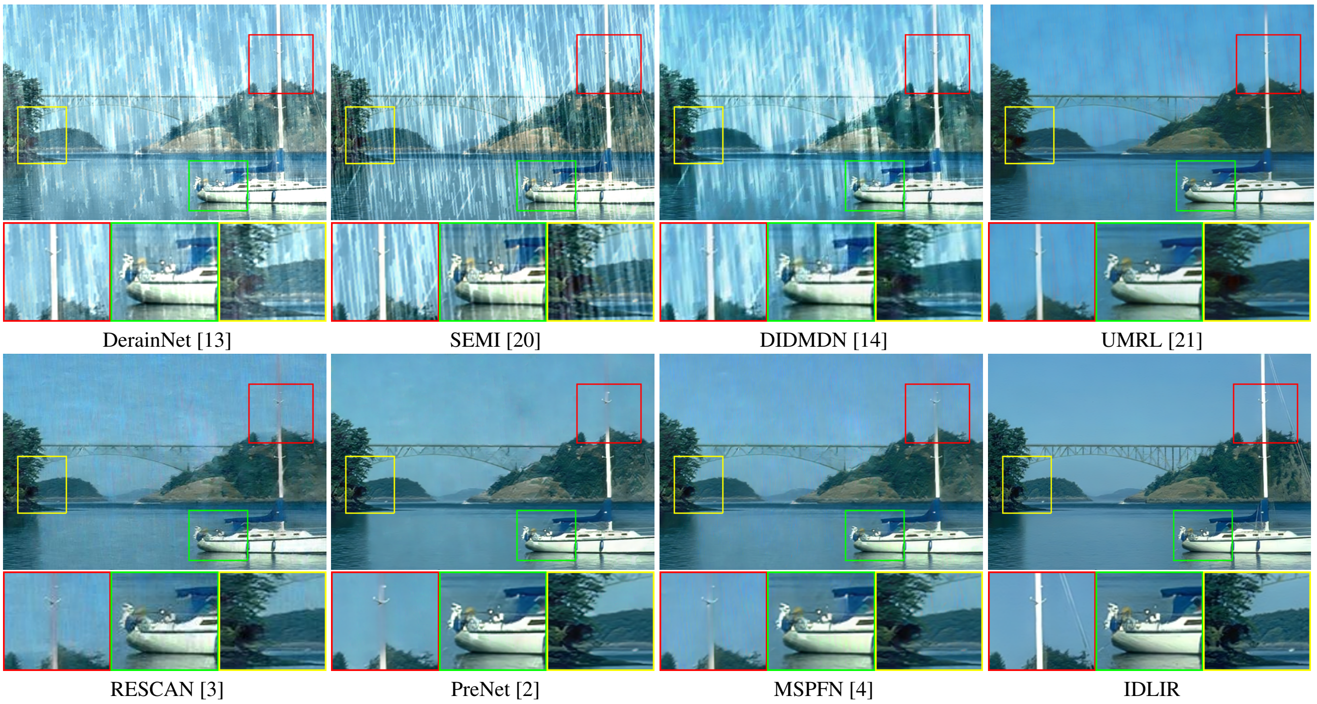

Fig. 2. Deraining results of IDLIR and the competing methods. The results by other competing methods are over-smoothed or suffer from dark artifacts, while our IDLIR produces visually favorable deraining result.

performance gains then state-of-the-art methods. In terms of visual quality, our IDLIR can remove rain streaks more clear, while maintaining texture details of background image. In contrast, these competing methods tend to over-smooth texture details or suffer from severe dark artifacts, as shown in Fig. 2.

4.3. Evaluation with Image Denoising

On image denoising task, our IDLIR is compared with DnCNN, MLP, BM3D, CBDNet, RIDNet, AINDNet, VDN, SADNet, DANet+ and CycleISP. We used 32 high-resolution images on the SSID [24] data set to train our model, evaluation is conducted on 1,280 validation patches from SIDD [24] and DND [25]. As reported in Table 2, our IDLIR performs better than competing methods in terms of PSNR, and is comparable in terms of SSIM. From Fig. 3, our IDLIR can obtain satisfying denoising results for real-world noisy images.

4.4. Ablation study

In this subsection, we take image deraining on Rain100H [19] as testing bed to analyze our IDLIR. Ablation studies include the effectiveness of degradation learning, number of iterations and different loss functions.

Learning degradation model. In existing deraining methods, the deraining model defaults to the linear superposition process of the background image X and the rain streaks Y. In our IDLIR, we adopt degradation network $\mathcal{F}$ to learn degradation model from training samples. We train one IDLIR model by replacing $\mathcal{F}$ as linear degradation model, i.e.,

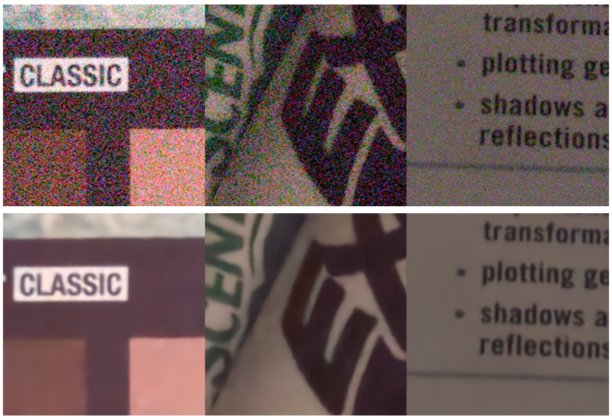

Fig. 3. Denoising results by our IDLIR method.

Table 2. Evaluation on image denoising task. These methods are trained SIDD training set, and evaluated on testing sets of SIDD and DND.

Methods	SIDD [24]	DND [25]
DnCNN [6]	23.66/0.583	32.43/0.790
MLP [27]	24.71/0.641	34.23/0.833
BM3D [28]	25.65/0.685	34.51/0.851
CBDNet [29]	30.78/0.801	38.06/0.942
RIDNet [30]	38.71/ 0.951	39.26/0.953
AINDNet [31]	38.95/0.952	39.37/0.951
VDN [32]	39.28/0.956	39.38/0.952
SADNet [7]	39.46/0.957	39.59/0.952
DANet+ [8]	39.47/0.957	39.58/0.955
CycleISP [33]	39.52/ **0.957**	39.56/**0.956**
IDLIR	**41.90**/ 0.952	**39.68**/0.955

Table 3. Ablation studies of degradation model and number of iterations.

	Degradation Model		Iterations		
	Liner	$\mathcal{F}$	$N=3$	$N=4$	$N=5$
PSNR	31.30	32.62	31.59	31.73	32.62
SSIM	0.920	0.935	0.927	0.927	0.935

X^n and Y^n are directly added to obtain Z^n. As reported in Table 3, our IDLIR can achieve much better than the variant model with linear degradation model.

Number of iterations. We set the number of iterations of the model to 3, 4, and 5 respectively, and then evaluate their quantitative performance. The experiment proves that with increasing the number of iterations, the performance of the IDLIR model will increase. However, when the number of iterations exceeds 5, the performance does not improve. These results by IDLIR models exceeding 5 iterations are not reported, and in this paper we set the default number of iterations as 5.

Loss function. We designed three different loss functions to train the network, i.e., $\mathcal{L}_1^{MSE}$ by setting ℓ in $\mathcal{L}_1$ as MSE, $\mathcal{L}_1^{-SSIM}$ by setting ℓ in $\mathcal{L}_1$ as negative SSIM, and $\mathcal{L}_2^{-SSIM}$ by setting ℓ in $\mathcal{L}_2$ as negative SSIM. From Table 4, one can see that negative SSIM can contribute to performance gains than MSE. And by only imposing supervision on latent clean image as $\mathcal{L}_2$ is a better choice than imposing supervision on both latent clean image and reconstructed degraded image as $\mathcal{L}_1$. Finally, we adopt $\mathcal{L}_2^{-SSIM}$ as the learning objective to train our IDLIR models.

Table 4. Ablation studies of loss functions

	$\mathcal{L}_2^{-SSIM}$	$\mathcal{L}_1^{-SSIM}$	$\mathcal{L}_1^{MSE}$
PSNR	32.62	31.86	31.57
SSIM	0.935	0.926	0.925

5. CONCLUSION

In this paper, we proposed to integrate degradation learning into image restoration, where latent clean image and degradation map are iteratively recovered and are fused by a degradation network to form reconstructed degraded image. For image denoising and image deraining, the proposed IDLIR performs better than state-of-the-art methods on several benchmark datasets. In future, IDLIR can be further applied to handle more image restoration tasks, such as image deblurring, image dehazing, etc.

6. ACKNOWLEDGEMENT

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