ABSTRACT

Image restoration is the task of recovering a clean image from a degraded version. In most cases, the degradation is spatially varying, and it requires the restoration network to both localize and restore the affected regions. In this paper, we present a new approach suitable for handling the image-specific and spatially-varying nature of degradation in images affected by practically occurring artifacts such as blur, rain-streaks. We decompose the restoration task into two stages of degradation localization and degraded region-guided restoration, unlike existing methods which directly learn a mapping between the degraded and clean images. Our premise is to use the auxiliary task of degradation mask prediction to guide the restoration process. We demonstrate that the model trained for this auxiliary task contains vital region knowledge, which can be exploited to guide the restoration network’s training using attentive knowledge distillation technique. Further, we propose mask-guided convolution and global context aggregation module that focuses solely on restoring the degraded regions. The proposed approach’s effectiveness is demonstrated by achieving significant improvement over strong baselines.

1 Introduction

Image restoration is a task of learning a mapping function that transforms input degraded images into enhanced images devoid of the artifacts and distortions. Due to the complexity of scene contents and weather conditions, image degradation is often inevitable. Such degradations impact not only human visibility but also degrade many computer vision applications, such as autonomous driving, drone flying, and surveillance systems, etc. As in many other computer vision tasks, the employment of deep convolutional networks has made significant progress. Given a large number of original and restored image pairs, the task can be solved by image-to-image translation methods, which have made considerable progress. In this study, aiming at further improvements, we pursue a different design that explores the importance of degraded-region detection and show that this approach is equally beneficial for various tasks of image restoration.

Existing CNN-based methods for image restoration employ a single network while focusing on the effectiveness of different baseline architectures [Jiao et al. 2017], [Zhang et al. 2019], enlarging the receptive field [Liu et al. 2018a], using multi-scale information [Fan et al. 2019], feature exploitation etc. However, the fact that the spatial scales and orientations of the degradations may vary across an image is mostly overlooked by existing methods. Intuitively, image restoration can be explained as a combination of two tasks - detection and then the restoration of affected parts of an image. In this work we address the task of removing complex spatially varying image degradations. Such degradations usually arise due to the medium between the camera and the scene and the dynamics of the scene with respect to camera. Bad weather causes significant image quality and visibility degradation in form of rain. These tasks are highly spatially varying due to non uniform depth variations, rain streaks’ directions and locations (rain-streak). Directly regressing from degraded to clean image becomes a challenging task, and training a single network with this objective limits the restoration quality. We claim that it is equally necessary to accurately localize the regions which are affected and having prior knowledge of the affected areas significantly helps a restoration network. Few recent approaches also have explored the utility of auxiliary information like edge [Nazeri et al. 2019], depth-map [Li et al. 2020], etc., which are tailored for a particular task. For constructing a general approach that will be equally effective for any of the spatially varying restoration tasks, instead of using any particular guidance like object boundaries, segmentation, etc., we propose to localize the affected regions first and then use this region knowledge to guide the restoration process effectively. We demonstrate the efficacy of our approach for removing these atmospheric degradations and claim that it can be equally
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effective for any restoration task with highly spatially-varying nature, and we choose dynamic scene deblurring as an additional application, where depth variations and moving objects results in spatially varying degradation.

Following [Wang et al. 2019], [Qian et al. 2018], we take the difference between the ground-truth and the input image and threshold it to generate the ground-truth degradation masks. Intuitively these masks denote the regions with significant degradation, which are difficult to restore. In the first step, we pre-train a mask prediction module with the same structure as the restoration network but with much fewer layers for a simpler binary classification task. Next, we focus on extracting the knowledge from the mask-prediction network and improve the original restoration task.

We propose to use attentive-distillation technique to extract relevant intermediate feature-level information from the mask prediction network and try to transfer this knowledge to the restoration network. Intuitively, it can be related to a type of transfer learning problem where the target domain is identical to the source domain, but the target task is different from the source task [Pan and Yang 2009]. We show that features extracted by the mask prediction network can act as better localization cues and can be exploited as additional supervision to the restoration-encoder (Sec. 3.1). The intuition behind this design choice is that the mask-encoder should excel at extracting features with rich information about the degraded regions, and the restoration-encoder can learn its behavior to obtain more useful features with better region information. We further allow the restoration encoder to adaptively calibrate its attention towards only the relevant and most useful features of the mask-encoder.

We also demonstrate that the predicted mask can be exploited to improve the restoration performance further while requiring slightly more parameters for the mask prediction network at inference time. Apart from implicit knowledge transfer from the mask prediction network, the mask itself can be utilized in the decoder to help restoration. We show the efficacy of mask-guided modules in the decoder to guide the restoration process with the predicted mask explicitly. (4) Our experiments demonstrate the effectiveness of the proposed approach for multiple restoration tasks. We claim these techniques can be incorporated for any general spatially varying image restoration problem to improve the performance significantly.

2 Related Works

Rain-streak removal Conventional image deraining methods adopt a model-driven methodology utilizing physical properties of rain and prior knowledge of background scenes into an optimization problem. Early approaches proposed use of pre-defined filters [Ding et al. 2016], priors [Zhu et al. 2017], layer separation model [Li et al. 2016], or screen blend model [Luo et al. 2015]. CNN-based methods significantly advanced the state-of-the-art in deraining [Fu et al. 2017] proposed a synthetic large-scale rain-streak dataset and used it to learn an end-to-end negative residual mapping using a 3-layer CNN. [Yang et al. 2017] constructed a more diversified dataset and deeper CNN architecture which takes advantage of larger receptive field using dilation filters, improving the deraining results by jointly detecting and removing rain-streaks.

Motion blur removal Motion deblurring is a challenging problem in computer vision due to its ill-posed nature. Major efforts have gone into designing priors that are apt for recovering the underlying undistorted image and the camera trajectory [Lai et al. 2016]. However, these methods preclude commonly occurring real-world blur arises from various sources including moving objects, camera shake and depth variations, causing different pixels to acquire different motion trajectories. A significant number of works have been proposed (Paramanand and Rajagopalan [2011], Nimisha et al. 2018a, Rao et al. [2014], Nimisha et al. [2018b], Vasu and Rajagopalan [2017], Paramanand and Rajagopalan [2014], Vijay et al. [2013]) where various traditional approaches were adopted for deblurring. Recent works (Purohit et al. 2019, Purohit and Rajagopalan [2020], [Mohan et al. 2021, 2019], [Vasu et al. 2018a] based on deep convolutional neural networks (CNN) have studied the benefits of replacing the image formation model with a parametric model that can be trained to emulate the non-linear relationship between blurred-sharp image pairs. Similar approaches can be found for image super-resolution [Suresh and Rajagopalan 2007], [Vasu et al. 2018b], Bhavsar and Rajagopalan [2010, 2012], Rajagopalan et al. [2005], Rajagopalan and Kiran [2003], Nimisha and Rajagopalan [2021], Purohit et al. [2020], Punnappurath et al. [2017, 2015]) and rolling shutter deblurring (Rengarajan et al. [2017] 2016a, Kandula et al. [2020], [Vasu et al. 2018c, 2017], [Mohan et al. 2017], [Rengarajan et al. 2016b], [Pichaikuppan et al. 2014]). Locally linear blur kernel assumption is explored in [Sun et al. 2015, Gong et al. 2017] with limited success.
in general dynamic scenes. Use of fully convolutional CNNs to directly estimate the latent sharp image was proposed in Nah et al. [2017] and adopted by recent works. Nah et al. [2017], Tao et al. [2018], Gao et al. [2019] proposed encoder-decoder residual networks to aggregate features in a coarse-to-fine manner, while showing benefits of selective parameter/feature sharing and/or recurrent layers. Zhang et al. [2018] explored a design composed of multiple CNNs and RNN. Recently, Zhang et al. [2019] proposed a multi-patch hierarchical network and stacked its copies along depth to achieve state-of-the-art performance.

3 Method

One of the most widely employed network architectures in image-to-image tasks is the encoder-decoder architecture Ronneberger et al. [2015]. It has showed its efficacy in image inpainting Liu et al. [2018b], semantic image segmentation Isola et al. [2017], image deblurring Tao et al. [2018], etc. In this paper, to make our approach as general as possible, we select a standard encoder-decoder model as the baseline for all the restoration tasks addressed. A detailed layerwise description of the network is given in supplementary material. Similarly, we deploy a very lightweight version of the encoder-decoder model (with similar level and structure) as the mask prediction network. This is because the task of binary classification is much simpler than the intensity regression task. We first train the mask prediction module using binary cross-entropy loss to predict the severely degraded regions. On the second step, we train a restoration network that actually carries out the restoration process utilizing the already available knowledge of the degraded regions. We also use a pixel-shuffling layer at the beginning that transforms the image pixels to channel-space using pixel-shuffling by a factor of 2. This allows subsequent computationally intensive operations to be performed at lower spatial resolution.

3.1 Knowledge-transfer

Information transferability in different layers was explored by Yosinski et al. [2014], e.g., the first layers learn general features like shape or structure, the middle layers learn high-level semantic features, and the last layers learn the features that are very specific to a particular task. We mainly focus on the encoders to convey knowledge about the regions that need to be restored. If the outputs from the $l^{th}$ layer of the mask encoder and restoration encoder are $x_l^*$ and $x_l$, then regularizing term can be defined as:

$$R(\theta, x)^{L,l} = ||x_l - x_l^*||_2^2$$

where $x$ is the input, and $\theta$ is the parameters of the restoration network. We regularize the “Behavior,” i.e., feature maps rather than model parameters. We want the guided layer in the restoration encoder to extract the relevant information from the hint layer of the mask-encoder using knowledge distillation. We use the down-sampling layers of the network as the breakpoints.

We also use meta-networks Jang et al. [2019] to decide which feature maps (channels) of the mask model are useful and relevant for the particular restoration task and which mask layers should be transferred to which restoration layers (Fig. 1). If there are $m$ encoder level/breakpoints, for each of the $m \times m$ pair, we introduce transfer importance predictor, which enforces different penalties for each channel according to their utility on the target task. For any particular pair, Eq. 1 can be modified as

$$R(\theta, x, \rho^{p,q})^{p,q} = \sum_{c \in C} \rho_c^{p,q}(x_q^*||((x_p - x_q^*)_c)||^2_2$$

where $\rho$ is the hyperparameter.
where \( p, q \in \{1, m\} \) and \( \rho_{c}^{p,q} : \mathbb{R}^{C \times H \times W} \rightarrow \mathbb{R}^{C} \) is the non-negative weight of channel \( c \) with \( \sum_{c \in C} \rho_{c}^{p,q} = 1 \). For any tensor \( z \), the term \( z_{c} \) denotes the \( c^{th} \) slice of the tensor. Similarly we denote the importance of each pair as \( \alpha_{p,q}^{c} : \mathbb{R}^{C \times H \times W} \rightarrow \mathbb{R}^{1} \geq 0 \). The combined transfer loss given the weights of channels \( \rho \) and weights of matching pairs \( \alpha \) is

\[
R = \sum_{(p,q) \in (m,m)} \alpha_{p,q}^{c}(x^{*}) R(\theta, x, \rho^{l,l})^{p,q}
\]  

(3)

Note that we suitably apply spatial interpolation/1 \( \times 1 \) convolution to match the feature pair’s dimension.

### 3.2 Mask-guided Convolution

Feature-wise masking has been explored extensively in many tasks. [Hu et al., 2018] re-calibrate feature responses by explicitly multiplying each channel with a learned sigmoidal mask. Recently in image inpainting, few methods advocate using masked convolution operation to reduce the impact of invalid pixels or holes. [Liu et al., 2018b] categorizes all input locations as either invalid or valid and multiplies a zero-or-one mask to inputs throughout all layers. For general image restoration task, we demonstrate the efficacy of gated convolution technique where we use the predicted mask to focus on restoring the degraded regions. Given the input feature map, \( x \) and the predicted-mask \( M \), the output can be calculated as

\[
f' = (W^{T} f) \odot M
\]  

(4)

where \( W \) is the weight of the convolutional layer.

### 4 Experiments

#### 4.1 Training description:

The restoration network minimizes \( l_{1} \) reconstruction loss between the network output and the GT clean image along with attentive distillation loss (Eq. 3). The degradation-mask estimator is trained using binary cross entropy loss with respect to the GT binary mask. Each training batch contains randomly cropped RGB patches of size \( 256 \times 256 \) from degraded images and we randomly flip them horizontally or vertically as the inputs. The batch-size was 8 for rain-streak removal and 16 for deblurring. Both stages use Adam optimizer with initial leaning rate \( 10^{-4} \), halved after every 50 epochs. We use PyTorch library and Titan Xp GPU.

#### 4.2 Datasets

**Rain-streak:** We utilize a challenging benchmark datasets in our experiments on rain streak removal viz. Rain100H [Yang et al., 2017]. Rain100H dataset contains of 1800 labeled images for training and 100 images for testing. Following the training and testing dataset split described in [Yang et al., 2017], our model is evaluated quantitatively using PSNR and SSIM scores on the luminance channel on Rain100H dataset.

**Motion blur:** We follow the configuration of [Zhang et al., 2019, Kupyn et al., 2019, Tao et al., 2018, Kupyn et al., 2017, Nah et al., 2017], which train on 2103 images from the GoPro dataset [Nah et al., 2017]. Also for testing, we use: GoPro [Nah et al., 2017] (1103 HD images).

#### 4.3 Rain-streak Removal

![Figure 2: Qualitative comparison of zoomed-in results on synthetic rainy images from the Rain100H test-set.](image)
Various existing methods are included in comparisons, including representative traditional methods including DSC Luo et al. [2015] and GMM Li et al. [2016], and several state-of-the-art deep CNN-based models i.e., DDN Fu et al. [2017], JORDER Yang et al. [2017], DDN Fu et al. [2017], JBZhu et al. [2017], DID-MDN Zhang and Patel [2018], RESCAN Li et al. [2018], PreNet Ren et al. [2019], and SPANet Wang et al. [2019]. Derained image results provided by the respective authors were used for Rain100H dataset.

As can be inferred from Table 1 our network achieves significant PSNR gains over all the competing methods. Learning-based deraining methods perform better than traditional techniques. Representative results from selected test images from Rain100H dataset are provided in Fig. 2. It can be seen that the visual quality of our results is significantly higher than that of state-of-the-art methods which contain visible rain streaks or missing textured regions.

### 4.4 Motion Blur Removal from Dynamic Scenes

We further validate our approach for general dynamic scene deblurring. Due to the complexity of the blur present in such images, conventional image formation model based deblurring approaches struggle to perform well. We provide extensive comparisons with Whyte et al. [2012] (representative traditional non-uniform deblurring model) and state-of-the-art learning-based methods, namely MS-CNN Nah et al. [2017], DeblurGAN Kupyn et al. [2017], DeblurGAN-v2 Kupyn et al. [2019], SRN Tao et al. [2018], and Stack(4)-DMPH Zhang et al. [2019]. Official implementation from the authors were used with default parameters.

The average PSNR and SSIM scores on GoPro test set are listed in Table 2. We compare against all existing models trained on GoPro train-set for fair comparisons.

Visual comparisons on images containing dynamic and 3D scenes are shown in Figs. 3. We observe that the results of prior works suffer from incomplete deblurring or artifacts. In contrast, our network demonstrates large dynamic blur handling capability while preserving sharpness. Scene details in the regions containing text, object boundaries, and textures are more faithfully restored, making them recognizable.

**Figure 3:** Visual comparisons of deblurring results on images from the GoPro test set [Nah et al. 2017]. Key blurred patches are shown in (b), while zoomed-in patches from the deblurred results are shown in (c)-(h).

### 5 Conclusion

We addressed the task of removing degradations from an image and show that our approach can generalize well to any image restoration task that is spatially varying in nature. We take an off-the-shelf encoder-decoder architecture.
as our strong backbone. We model the restoration task as a combination of degraded-region segmentation and region guided restoration. We propose a distillation technique for image restoration where we leverage the knowledge of a degradation mask prediction module as extra guidance. We show that this training strategy achieves superior results over the baseline for all of the tasks addressed without requiring any extra parameters at inference. Refined and complete version of this work appeared in IEEE-JSTSP.

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