

Dark and Bright Channel Prior Embedded Network for Dynamic Scene Deblurring

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Abstract—Recent years have witnessed the significant progress on convolutional neural networks (CNNs) in dynamic scene deblurring. While most of the CNN models are generally learned by the reconstruction loss defined on training data, incorporating suitable image priors as well as regularization terms into the network architecture could boost the deblurring performance. In this work, we propose a Dark and Bright Channel Priors embedded Network (DBCPeNet) to plug the channel priors into a neural network for effective dynamic scene deblurring. A novel trainable dark and bright channel priors embedded layer (DBCPeL) is developed to aggregate both channel priors and blurry image representations, and a sparse regularization is introduced to regularize the DBCPeNet model learning. Furthermore, we present an effective multi-scale network architecture, namely image full scale exploitation (IFSE), which works in both coarse-to-fine and fine-to-coarse manners for better exploiting information flow across scales. Experimental results on the GoPro and Köhler datasets show that our proposed DBCPeNet performs favorably against state-of-the-art deep image deblurring methods in terms of both quantitative metrics and visual quality.

Index Terms—Dynamic scene deblurring, Convolutional neural network, Dark and bright channel priors, Multi-scale strategy

I. INTRODUCTION

REPRODUCING the visual richness of a real-world scene is an essential goal of digital photography. The real images, however, are often blurred during image acquisition due to the effect of many factors such as camera shake, object motion, and out-of-focus [1]. The resulting blurry images will not only degrade the perceptual quality of photos but also degenerate the performance of many image analytic and understanding models [2]. Blind image deblurring, which has been studied extensively in low level vision for decades [3], plays an essential role in improving the visual quality of real-world blurry images.

In general, the purpose of blind image deblurring is to recover the latent sharp image \mathbf{y} from its blurry observation: $\mathbf{x} = \mathbf{k} \otimes \mathbf{y} + \mathbf{n}$, where \mathbf{k} is an unknown blur kernel (*i.e.*, uniform or non-uniform), \mathbf{n} is an additive white Gaussian noise and \otimes denotes the convolution operator. This inverse problem, however, is severely ill-posed and requires extra information on latent image \mathbf{y} to constrain the solution space. Thus, there are mainly two categories of approaches for utilizing prior

knowledge, *i.e.*, optimization-based and deep learning based deblurring methods. Optimization-based approaches explicitly model prior knowledge to regularize the solution space of blur kernel [4], [5], [6], [7], [8] and latent image [9], [10], [11], [12], [13] via an optimization framework. In contrast, deep learning based methods [1], [2], [14], [15] implicitly learn a direct mapping function (*e.g.*, convolutional neural network, CNN) from degraded image to latent clear image.

For the blind image deblurring problems, optimization-based and deep learning-based methods respectively have their merits and limitations. Optimization-based methods are flexible in incorporating versatile priors or regularizations [4], [5], [8], [11], [12] tailored for blind deblurring, but suffer from the time-consuming optimization procedure and oversimplified assumptions on blur kernels (*e.g.*, spatially invariant and uniform). Moreover, conventional image priors (*e.g.*, total variation [4]) are limited in blind deblurring and prone to the ordinary solution of delta kernel. Stronger priors, *e.g.*, ℓ_0 -norm [16] and normalized sparsity [5], are then suggested for blur kernel estimation. On the other hand, deep learning methods [1], [2], [14], [15] benefiting from end-to-end training and joint optimization enjoy fast speed and flexibility in handling spatially variant blur in the dynamic scene. However, deep models may be limited in capturing specific priors for blind deblurring. As for dynamic scene deblurring, existing dataset [1] is of a relatively small scale, hindering the performance of learned model.

Taking the merits and drawbacks of optimization-based and deep learning-based methods into account, one interesting question is that can we exploit prior models to constrain the network architecture and/or loss functions for deblurring performance improvement? Motivated by the effectiveness of image prior in blind deblurring, in this paper, we propose a Dark and Bright Channel Priors embedded Network (DBCPeNet) to help the restoration of latent clear image. The key component of DBCPeNet is a novel trainable dark and bright channel priors embedded layer (DBCPeL), which can aggregate both channel priors and blurry image representations to leverage their respective advantages. By enforcing sparsity on both dark and bright channels of feature maps, we can regularize the solution space of CNN during training, thereby incorporating channel priors into DBCPeNet.

Moreover, existing deep dynamic scene deblurring models [1], [14] usually adopt the multi-scale network architecture to exploit coarse and middle level information for finer scale image deblurring. However, these deep multi-scale network architectures only consider the coarse-to-fine information flow. That is, blind deblurring is first performed on the small

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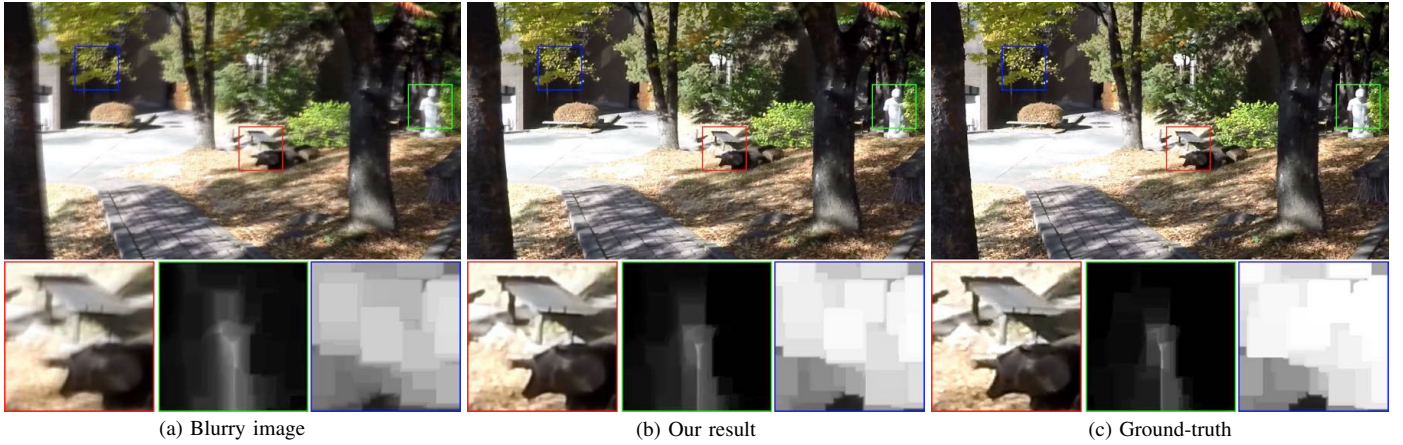


Fig. 1: Deblurring result on a GoPro image [1]. (a) The blurry image; (b) our result; and (c) the Ground-truth image. Red box: zoom-in view of the original local patch. Green box: zoom-in view of the dark channel of its corresponding local patch. Blue box: zoom-in view of the bright channel of its corresponding local patch.

scale, and then deblurring results (or latent representations) are combined with feature representations on a larger scale for further refinement. Unfortunately, such a multi-scale network architecture could not fully exploit the information flow across scales. In this work, we show that feature representations of larger scales actually can also benefit the dynamic scene deblurring on a smaller scale. To this end, we present a more effective multi-scale network architecture that works in both coarse-to-fine and fine-to-coarse manners. By training the deblurring network in this new multi-scale network structure, which we call image full scale exploitation (IFSE), we can better exploit the information flow across scales.

Experimental results on GoPro [1] and Köhler [17] datasets demonstrate that our DBCPeNet outperforms state-of-the-art deep dynamic scene deblurring methods. As shown in Figure 1, one can see that the dark and bright channels of our deblurring result are sparser than the blurry image. The contribution of this paper is two-fold:

- We propose a novel trainable structural layer, namely dark and bright channel priors embedded layer (DBCPeL), which can aggregate data information and prior knowledge (*i.e.*, priors on dark and bright channels) to leverage their merits but avoid limitations. DBCPeL provides an effective way to plug prior knowledge (*i.e.*, statistical properties) into a deep deblurring network in an end-to-end manner.
- We introduce a new multi-scale network structure, namely image full scale exploitation (IFSE), which works in both coarse-to-fine and fine-to-coarse manners to fully exploit different resolution images for maximizing the information flow.

The remainder of this paper is organized as follows. Section II briefly reviews the relevant works of optimization based deblurring methods and deep learning based deblurring methods. Section III presents the proposed DBCPeNet for aggregating both data information and channel prior knowledge. Section IV presents the experimental results, and Section V provides some concluding remarks.

II. RELATED WORK

In this section, we briefly review the recent optimization-based and deep learning based image deblurring methods.

A. Optimization-based Deblurring Methods

The optimization-based methods aim to develop effective image priors to favor clear images over the blurry one. Representative priors include sparse gradients [9], [18], [19], [20], hyper-Laplacian prior [21], normalized sparsity prior [5], ℓ_0 -norm prior [16], patch recurrence prior [22] and discriminatively learned prior [8], [13]. Taking advantage of the aforementioned priors, existing optimization-based methods could deliver competitive results on generic natural images. These approaches, however, cannot be generalized well to handle domain specific images. Thus, specific priors are introduced for specific images, *e.g.*, light streak prior [23] for low light images, and a combination of intensity and gradient prior [24] for text images. Recently, Pan *et al.* [11] developed the dark channel prior (DCP) [25] to enforce sparsity on the dark channel of latent image and achieved promising result on both generic and specific images. With the success of [11], Yan *et al.* [12] further introduced a bright channel prior (BCP) to solve the corner case image, which contains a large amount of bright pixels. By plugging the channel priors (a combination of BCP and DCP) into the deblurring model, Yan *et al.* achieved state-of-the-art results on various scenarios.

Although the optimization based algorithms have demonstrated their effectiveness in image deblurring, the simplified assumptions on the blur model and time-consuming parameter-tuning process are two lethal problems to hinder their performance in real-world cases. In this work, we utilize a realistic GoPro dataset [1] to end-to-end train a new multi-scale network for latent sharp image restoration. To make the learning of image representations more effective, the proposed network imposes dark and bright channel priors and sparse constraint in the feature domain.



Fig. 2: The dark and bright channels of the blurry and ground-truth images.

B. Deep Learning based Deblurring Methods

Deep learning based methods focus on exploiting external training data to learn a mapping function in accordance with the degradation process [26], [27]. The powerful end-to-end training paradigm and the non-linear modeling capability make CNNs a promising approach to image deblurring. Early CNN-based deblurring methods aim to mimic conventional deblurring frameworks for the estimation of both latent image and blur kernel. Prior works [28], [29] first use a network to predict the non-uniform blur kernel and then utilize a non-blind deblurring method [30] to restore images. In [31], Schuler *et al.* introduced a two-stages network to simulate iterative optimization. In [32], Chakrabarti *et al.* utilized a network to predict frequency coefficients of blur kernels. However, these methods may fail when the estimated kernel is inaccurate [33]. Therefore, more recent approaches prefer to train kernel estimation-free networks to restore latent images directly. Specifically, Nah *et al.* [1] proposed a multi-scale CNN to progressively recover the latent image. Tao *et al.* [14] introduced a scale-recurrent network equipped with a ConvLSTM layer [34] to further ensure information flow between different resolution images. Kupyn *et al.* [2] adopted the Wasserstein GAN [35], [36] as an objective function to restore the texture details of latent image. Zhang *et al.* [15] employed spatially variant recurrent neural networks (RNNs) to reduce the computational cost.

Considering that the limited amount of training data and the disappreciation of prior knowledge are two main factors hampering the performance improvement, we propose to introduce the priors knowledge (*i.e.*, DCP and BCP) into CNN to regularize the solution space of clear images. In addition, a new multi-scale structure, which works in both coarse-to-fine and fine-to-coarse manners, is introduced to better exploit image information across scales.

III. DARK AND BRIGHT CHANNEL PRIORS EMBEDDED NETWORK

In this section, we introduce a dark and bright channel priors embedded network (DBCPeNet) for dynamic scene deblurring. To begin with, we first present the motivation of our proposed DBCPeNet. Then, we describe in detail the network architecture, followed by the definitions of our proposed image full scale exploitation (IFSE), dark and bright channel priors embedded layer (DBCPeL) and the objective function.

A. Motivation

Given a single blurry image x_i , existing CNN-based methods aim at learning a mapping function F_Θ to generate an estimation of latent sharp image \hat{y}_i , which is required to approximate the ground-truth y_i . This procedure can be formulated as:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \sum_i \ell(\hat{y}_i, y_i), \quad s.t. \quad \hat{y}_i = F_\Theta(x_i) \quad (1)$$

where (x_i, y_i) refer to the i -th image pair in the training dataset and Θ is the parameter of mapping function. However, such a formulation is limited in capturing image priors specified to blind deblurring, which is generally very different from those for non-blind restoration. Moreover, the existing training image pairs are insufficient to learn an effective mapping function F_Θ . Therefore, incorporating suitable image priors as well as regularization terms into the network architecture is essential to further improve the deblurring performance.

In [11], [12], it is argued that the dark/bright channel priors and sparse constraint favor clear images over the blurry ones, and this claim has been verified on natural images, as well as face, text, and low illumination images. In general, a blurred image can be modeled as the output of convolving a sharp image with (uniform or non-uniform) blur kernels, and the

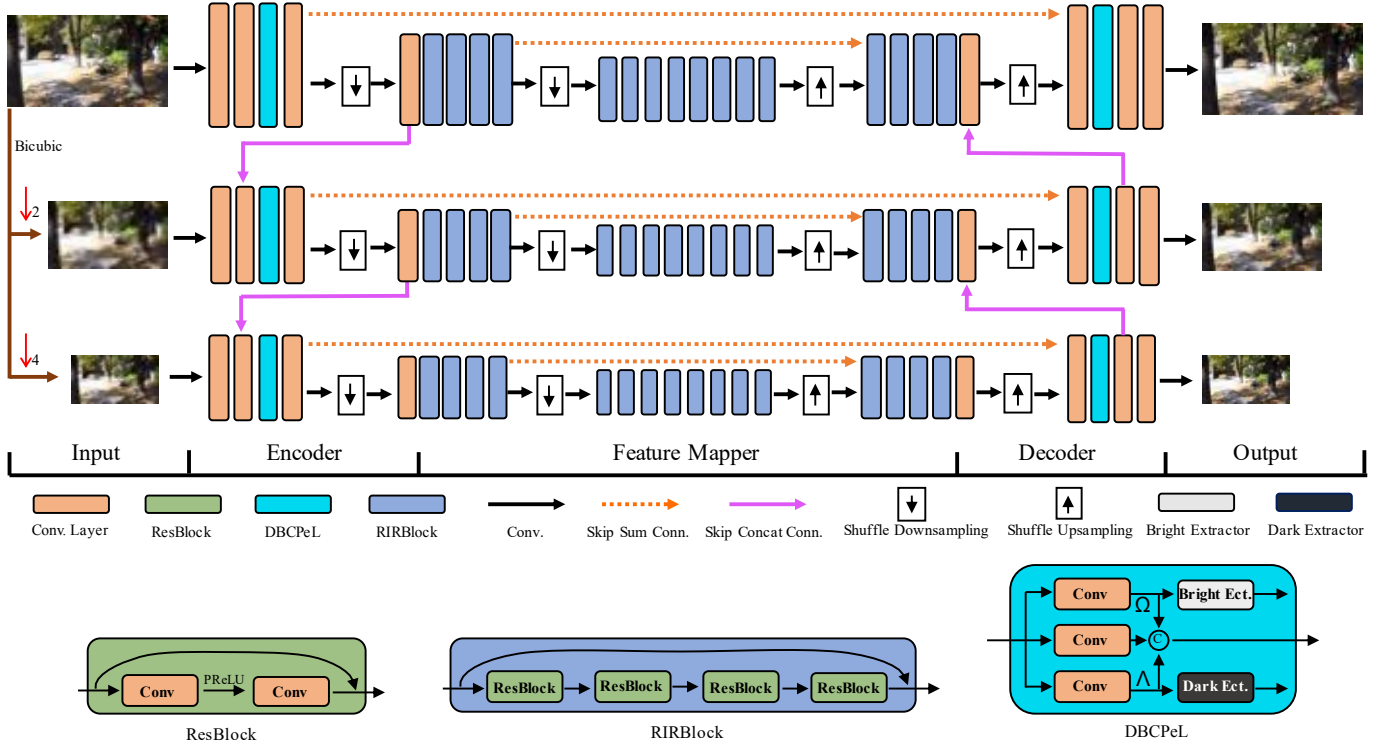


Fig. 3: Illustration of our proposed DBCPeNet architecture.

dark and bright channels are formed by the highest and lowest values across the RGB channels. As described in [25], [11], [12], the dark channel $D(\cdot)$ and the bright channel $B(\cdot)$ are defined as:

$$\begin{aligned} D(I)(x) &= \min_{y \in \Omega(x)} \left(\min_{c \in \{r, g, b\}} I^c(y) \right) \\ B(I)(x) &= \max_{y \in \Omega(x)} \left(\max_{c \in \{r, g, b\}} I^c(y) \right) \end{aligned} \quad (2)$$

where I is a given image, x and y denote pixel locations, $\Omega(x)$ is a local patch centered at x , and I^c is a color channel of image I .

Since a dark/bright pixel will be averaged with its neighboring high/low intensity pixels during the blurring process, the dark channel of a blurred image would be less dark and the bright channel would be less bright, as illustrated in Figure 2. Inspired by [11], [12], we find that enforcing sparsity on the feature representations of dark and bright channels favors clear images over blurred ones. Thus, we propose a novel trainable DBCPeL that aggregates both blurry image and dark/bright channel representations to enhance deblurring performance. Then, the Eqn. (1) can be rewritten as:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \sum_i \ell(\hat{\mathbf{y}}_i, \mathbf{y}_i), \quad \text{s.t. } \hat{\mathbf{y}}_i = F_{\Theta}(\mathbf{x}_i | \Lambda, \Omega) \quad (3)$$

where Λ and Ω are channel representations under the constraint of dark and bright channel priors. By this way, we embed the image priors into the mapping function F_{Θ} to generate higher quality latent sharp image.

B. Architecture

Most of the traditional deblurring methods and the CNN-based dynamic scene deblurring networks [1], [14] prefer to utilize the multi-scale structure where the coarse-to-fine strategy is used for handling blur kernel. However, we found that a larger scale feature representations can also benefit the dynamic scene deblurring at a smaller scale. A multi-scale network architecture that works in both coarse-to-fine and fine-to-coarse manners could help the network fully exploit the information flow across scales.

The overall architecture of our proposed DBCPeNet is illustrated in Figure 3. It contains three sub-networks respectively for three scales, and each of them consists of three major components: (i) input and output; (ii) encoder and decoder; (iii) feature mapper. Note that instead of utilizing the Rectifier Linear Units (ReLU) [37], we take the parametric ReLU (PReLU) [38] as activation function since it can improve the modeling capability with negligible extra computational cost. Unless denoted otherwise, all the convolution filters are set to 3×3 , instead of 5×5 as utilized by most of the other dynamic scene deblurring networks (*e.g.*, [1] and [14]). Although a filter of size 5×5 has more parameters than two filters of size 3×3 , the one utilizing 3×3 filters is more efficient and additional nonlinearity can be inserted between them [39]. The stride size for all convolution layers is set to 1 and the number of feature maps in each layer is set to 64, except for the last layer and the proposed DBCPeL, where the number of feature maps is set to 3 and $\{3, 64, 3\}$, respectively. The details of each component are described as follows.

Input and Output. An effective multi-scale network architec-

ture is utilized in this work to restore the latent sharp image from a coarser scale to finer scales. Consider an image pair $(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^{H \times W \times C}$, where $H \times W$ is the pixel resolution and C is the number of channels, which is set to 3. We first use bicubic interpolation to progressively downsample the image pair with the ratio of $\frac{1}{2}$, and generate 3 scales of image pairs with the resolution of $\{H \times W, \frac{H}{2} \times \frac{W}{2}, \frac{H}{4} \times \frac{W}{4}\}$. We then take those blurred images at each scale as inputs to produce their corresponding sharp images. The sharp one at the original resolution is considered as the final output.

Encoder and Decoder. Each scale of the encoder consists of 4 convolution layers, the proposed DBCPeL and a shuffle operation with factor $\frac{1}{2}$. As for the decoders, they basically mirror the architecture of the encoders, except that the factor of shuffle operation [40] is set to 2. The encoder and decoder networks are mainly designed for three purposes. (i) They progressively transform images on different scales to extract shallow features (in encoders) and transform them back to the resolution of inputs (in decoders). (ii) They work in both coarse-to-fine and fine-to-coarse manners for better exploiting information flow across scales. More details of the proposed multi-scale structure are described in Subsection III-C. (iii) They integrate both dark and bright channel priors into the network via DBCPeL for regularizing the model learning. More details of the proposed DBCPeL are presented in Subsection III-D.

Feature Mapper. The feature mapper module, which aims to refine the shallow features progressively, is an essential part of latent image restoration. One critical factor for reducing blur artifacts is the size of receptive field. To enlarge the receptive field, we (i) stack a set of convolutional layers to achieve a larger depth network and (ii) utilize the shuffle operations for downsampling and upsampling features. To ensure that a deeper neural network can converge to a local minimum, we adopt the residual blocks to speed-up the training procedure [41], [26]. Besides, the feature mapper module utilizes the long skip connection and short skip connection to make full use of hierarchical features in all convolutional layers. A similar skip connection strategy has been utilized in a very recent work [42]. As illustrated in Figure 3, the feature mapper contains 16 residual-in-residual blocks (RIRBlock), and each of them has 4 residual blocks (ResBlock). The ResBlock consists of 2 convolution layers and a PReLU activation function. Since we utilize the filter of size 3×3 , the total number of parameters of our DBCPeNet is almost the same as previous methods. Note that all the weights across different scales of feature mapper sub-modules are shared.

C. Image Full Scale Exploitation

To remove the large blur kernels, previous blind deblurring methods [43], [1], [14] often utilize the multi-scale strategy to progressively predict the blur kernel and the latent image. Generally, methods are first performed at the smallest scale of the blurry image to estimate its corresponding coarsest scale kernel and latent sharp image, and then the coarsest deblurring result is combined with the larger scale blurry input for further refinement. However, such a coarse-to-fine strategy

could not fully exploit the information flow across scales because we find that: (i) the information of finer scale blurry image representation is beneficial for the estimation of coarser scale latent sharp image; and (ii) the combination in shallow feature domain can yield a better result than image (RGB) domain. Unlike previous methods [1], [43], [14] that directly concatenate the upsampled coarser scale latent sharp image with the finer scale blurry image, we propose a new multi-scale structure, namely image full scale exploitation (IFSE), which works in both coarse-to-fine and fine-to-coarse manners to ensure the information flow across different scale images and expand the receptive field. Specifically, in the fine-to-coarse phase, the encoder first downsamples the finest scale latent image representations by shuffling the features with factor $\frac{1}{2}$ to ensure the same resolution on different scales of features (namely, a features of size $m \times n \times c$ is shuffled to $\frac{m}{2} \times \frac{n}{2} \times 4c$). Then the encoder further concatenates the downsampled features with coarser scale features for restoring the coarser scale sharp image. On the contrary, in the coarse-to-fine phase, the decoder upsamples the restored coarser scale features by shuffling the features of size $\frac{m}{2} \times \frac{n}{2} \times 4c$ back to $m \times n \times c$ and concatenates them with finer scale features to estimate the finer scale sharp image. Consequently, by training the network in both coarse-to-fine and fine-to-coarse manners, our proposed DBCPeNet can fully exploit different scale images to maximize the information flow between them, resulting in better performance. In Section IV-C, we will conduct an ablation study to verify its effectiveness.

D. Dark and Bright Channel Priors Embedded Layer

Since the dark and bright channels of a sharp image is sparser than a blurry image, the dark and bright channel priors and sparse constraints favor clear images over blurred images. Therefore, we propose an DBCPeL to aggregate blurry image representation and dark/bright channel representation together to regularize the solution space of CNN. Specifically, it first learns 3 mapping functions \mathcal{M}_θ , $\mathcal{M}_{[\alpha|D]}$ and $\mathcal{M}_{[\beta|B]}$ to transform the feature map f^{l-1} from previous layer into 3 new feature maps, including a deeper layer transformed feature f^l , a dark channel prior constrained feature Λ , and a bright channel prior constrained feature Ω . It then adopts a concatenation operation to concatenate those 3 feature maps for the integration of blurry image representation and dark/bright channels representation. Formally, the proposed DBCPeL can be expressed as:

$$\begin{aligned} [\Lambda, f^l, \Omega] &= \text{DBCPeL}(f^{l-1}) \\ f^l &= \mathcal{M}_\theta(f^{l-1}) \\ \Lambda &= \mathcal{M}_{[\alpha|D]}(f^{l-1}) \\ \Omega &= \mathcal{M}_{[\beta|B]}(f^{l-1}) \end{aligned} \quad (4)$$

where $[\Lambda, f^l, \Omega]$ denotes the concatenation of these feature maps, and the subscripts $[\alpha|D]$ and $[\beta|B]$ denote that the parameters α and β are optimized under the dark and bright channel priors constraint. To add dark and bright channel priors constraint into a network, the DBCPeL utilizes (i) extractors to extract both dark and bright channel of features, and (ii) the ℓ_1 -regularization term to enforce sparsity in training.

The extractor $D(\cdot)$ is designed to extract the dark channel of Λ via computing its minimum values in a local patch. Its forward function can be written as follows:

$$\begin{aligned} D(\Lambda)_{[h,w]} &= \Lambda_{[\mathcal{I}_{\mathcal{D}}[h,w]]} \\ \mathcal{I}_{\mathcal{D}}[h,w] &= \operatorname{argmin}_{i^* \in \Psi_{[h,w,c]}} \Lambda_{[i^*]} \end{aligned} \quad (5)$$

The extractor $B(\cdot)$ aims to extract the bright channel of Ω by calculating its maximum values in a local patch. Its forward function can be formulated as:

$$\begin{aligned} B(\Omega)_{[h,w]} &= \Omega_{[\mathcal{I}_{\mathcal{B}}[h,w]]} \\ \mathcal{I}_{\mathcal{B}}[h,w] &= \operatorname{argmax}_{i^* \in \Psi_{[h,w,c]}} \Omega_{[i^*]} \end{aligned} \quad (6)$$

where $\Psi_{[h,w,c]}$ is the index set of inputs in a sub-window centered at pixel location $[h, w, c]$, $\mathcal{I}_{\mathcal{D}}[h,w]$ and $\mathcal{I}_{\mathcal{B}}[h,w]$ are the masks that record the indices of the minimum and maximum values in a local patch, respectively. The patch sizes for each scale are set to $\{31 \times 31, 19 \times 19, 11 \times 11\}$. A single element $\Lambda_{[h,w,c]}$ or $\Omega_{[h,w,c]}$ of the input may be assigned to different outputs of $D(\Lambda)_{[h,w]}$ or $B(\Omega)_{[h,w]}$.

To ensure that the dark and bright channel priors can be end-to-end trained with the network, the gradient of each component should be calculated for back-propagation. The backward function of extractors computes the partial derivative of the loss function with respect to input variables Λ_i and Ω_i as follows:

$$\begin{aligned} \frac{\partial L}{\partial \Lambda_i} &= \sum_h \sum_w \sum_c 1\{i = \mathcal{I}_{\mathcal{D}}[h,w]\} \frac{\partial L}{\partial D(\Lambda)_{[h,w]}} \\ \frac{\partial L}{\partial \Omega_i} &= \sum_h \sum_w \sum_c 1\{i = \mathcal{I}_{\mathcal{B}}[h,w]\} \frac{\partial L}{\partial B(\Omega)_{[h,w]}} \end{aligned} \quad (7)$$

where i refers to the pixel location $[h, w, c]$. In other words, the partial derivatives $\frac{\partial L}{\partial D(\Lambda)_{[h,w]}}$ and $\frac{\partial L}{\partial B(\Omega)_{[h,w]}}$ are accumulated if i is the argmin and argmax selected for $D(\Lambda)_{[h,w]}$ and $B(\Omega)_{[h,w]}$, respectively. In back-propagation, the partial derivatives $\frac{\partial L}{\partial D(\Lambda)_{[h,w]}}$ and $\frac{\partial L}{\partial B(\Omega)_{[h,w]}}$ are already calculated by the backward function of the loss layer.

With the proposed DBCPeL, we can extract the dark and bright channels of shallow features (*i.e.*, $D(\Lambda)$ and $B(\Omega)$), which can be further enforced to be sparse via the objective function. By integrating the constrained features Λ and Ω into the network, the proposed DBCPeNet can achieve a better performance while using the same training dataset. The ablation study in Section IV-C is conducted for the evaluation.

E. Loss Function

We utilize an ℓ_1 -norm of the reconstruction error as loss function for each scale. More specifically, we rewrite Eqn. (3) as:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^3 \|\mathbf{y}_i^j - F_{\Theta}(\mathbf{x}_i^j | \Lambda^j, \Omega^j)\|_1 \quad (8)$$

where N is the total number of training pairs (\mathbf{x}, \mathbf{y}) and j is the number of scales, which is set to 3 in this paper. Symbol $(\cdot)^j$ refers to the image and feature on the j -th scale.

As described above, the sparsity regularization term is more beneficial for restoring a sharp image than a blurred one. To this end, we introduce an ℓ_1 -regularization term to enforce sparsity on both dark and bright channels of shallow features. The objective function can be given by:

$$\begin{aligned} \mathcal{L} &= \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^3 \|\mathbf{y}_i^j - F_{\Theta}(\mathbf{x}_i^j | \Lambda^j, \Omega^j)\|_1 \\ &\quad + \lambda \|D(\Lambda^j)\|_1 + \omega \|1 - B(\Omega^j)\|_1 \end{aligned} \quad (9)$$

where λ and ω are the trade-off parameters. $D(\cdot)$ and $B(\cdot)$ are the extractors to extract the dark channel and bright channel of features, respectively. With the forwards and backwards functions, the dark and bright channel extractors can be jointly optimized with the network in an end-to-end manner.

IV. EXPERIMENTAL RESULTS

In this section, we provide experimental results to show the advantage of our proposed DBCPeNet. We first present the experimental settings, including training and testing datasets, as well as parameter settings. We then compare DBCPeNet with state-of-the-art dynamic scene deblurring methods. Finally, we conduct the ablation studies to verify the effectiveness of our proposed DBCPeL and the IFSE strategy.

A. Experiment Settings

We implement our framework by using the Caffe toolbox [44], and train the model on a PC equipped with an Intel Core i7-7820X CPU, 128G RAM and a single Nvidia Quadro GV100 GPU. Code, trained models and the deblurring results on the GoPro and Köhler datasets can be downloaded at <https://github.com/csjaic/DBCPeNet>.

Datasets. The proposed DBCPeNet is trained on the GoPro training dataset [1], which contains 22 sequences with 2,103 blurred/clear image pairs. Once the model is trained, we test it on the GoPro testing dataset [1] and Köhler [17] dataset. It is worth pointing out that, following previous methods [1], [14], we use the linear subset of the GoPro dataset to train the network and test the model. The GoPro testing dataset consists of 11 sequences with 1,111 image pairs, and the Köhler dataset contains 4 latent images and 12 blur kernels. To simulate the realistic blurring process, the GoPro dataset generates blurred images through averaging 7 – 15 adjacent short-exposure frames captured by a high-speed video camera (240 fps), while the Köhler dataset replays the recorded 6D real camera motion trajectory to synthesize blurred images. In addition, we also test the proposed DBCPeNet on some of the real-world blurred images provided in [45]. Note that since the real-world blurred images in [45] do not have corresponding ground-truth images, only visual comparison results are given.

Parameter Settings. To train the DBCPeNet, we crop the GoPro training dataset into $256 \times 256 \times 3$ patches and take them as inputs. The mini-batch size in all the experiments is set to 10, and the trade-off parameters λ and ω are set to 0.1 and 0.2, respectively. The Xavier [46] is utilized to initialize the trainable variables. The Adam solver [47] with the default

parameters ($\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$) was adopted to optimize the network parameters. We fix the learning rate as 10^{-4} and train the network with 600K iterations. Additionally, we randomly rotate and/or flip the image patches for data augmentation. The 1% additive Gaussian noise is also randomly added to the blurred images for robust learning.

B. Comparisons with State-of-the-art Methods

In this subsection, both quantitative and qualitative evaluations are conducted to verify the proposed DBCPeNet on the benchmark datasets.

Quantitative Evaluations. Instead of uniform deblurring, where the blurred image is modeled as output of convolving a sharp image with a spatially invariant kernel, in this paper we focus on dynamic scene (non-uniform) deblurring, where the blurred image is modeled as convolving a sharp image with a set of spatially variant kernels. In other words, for different locations of the blurred image, the blur kernels are different. We followed the same experimental setting as the prior arts [1], [15], [14], and compared DBCPeNet with previous state-of-the-art deblurring methods [48], [28], [1], [2], [15], [14] in a quantitative way. A traditional dynamic scene deblurring method [48] is also used as one of the competitors. The source codes and trained models of the aforementioned methods can be downloaded at the authors' websites, except for [48] and [15] whose results have been reported in previous works [1] and [15], respectively. Additionally, we utilize the same training dataset to retrain the network provided by [15] for its evaluation on the Köhler dataset. The average PSNR, SSIM, and MSSIM indices for different deblurring methods on GoPro testing and Köhler datasets are shown in Table I. One can see that on the GoPro testing dataset, the proposed DBCPeNet significantly outperforms both the conventional non-uniform deblurring method [48] and these recently developed CNN based methods [28], [1], [2], [15], [14]. Even compared to the previous state-of-the-art method [14], the proposed DBCPeNet still has 0.84 dB improvement. While on the Köhler dataset, all these deep learning based dynamic scene networks (including our proposed DBCPeNet) trained on the GoPro dataset cannot achieve satisfactory results. This is mainly because the GoPro training dataset itself is not comprehensive enough to cover the different types of kernels. Moreover, the kernel distribution and the kernel size between GoPro and Köhler datasets are very different. Thus, these dynamic scene deblurring networks have comparative performance on the Köhler dataset. However, one can still notice that our method has certain advantage over competing methods.

Meanwhile, the running time by different methods for processing an image of resolution $1280 \times 720 \times 3$ is also listed in Table I. One can notice that it takes a lot of time for a conventional method to restore an image because of the time-consuming iterative inference and the CPU implementation. While for these end-to-end training networks, they can achieve much faster speed to process an image on GPU. Considering that these dynamic scene deblurring networks are implemented by different deep learning platforms, the minor difference between them can be neglected within the margin of error.

TABLE I: Average PSNR (dB), SSIM, MSSIM indices and runtimes for different methods on the benchmark datasets (running time is measured for an image with size $1280 \times 720 \times 3$).

Method	GoPro		Köhler		Time
	PSNR	SSIM	PSNR	MSSIM	
Kim [48]	23.64	0.824	24.68	0.794	1 hr
Sun [28]	24.64	0.843	25.22	0.774	20 min
Nah [1]	29.08	0.914	26.48	0.808	2.87s
Tao [14]	30.26	0.934	26.75	0.837	0.62 s
Kupyn [2]	28.70	0.858	26.10	0.816	0.59s
Zhang [15]	29.19	0.931	25.71	0.800	0.76s
Proposed	31.10	0.945	26.79	0.839	0.65s

Qualitative Evaluations. We compare the visual quality of restored images by our proposed DBCPeNet and these recently developed CNN based dynamic scene deblurring networks, including Nah [1], Tao [14], Kupyn [2], and Zhang [15]. Figures 4-6 shows several blurred images from the GoPro [1] testing dataset and their corresponding deblurring results produced by the above methods. One can see that although these recently developed CNNs could remove the overall motion blur artifacts, the results restored by them are not perceptually pleasing enough because of the blurred edges and noticeable artifacts. For example, in Figures 5, all these previous CNN based deblurring networks could not recover the text information (see the red box zoom-in region). While in Figures 6, noticeable artifacts appear around the human face. By contrast, benefiting from the dark and bright channels prior constraint, our method can deliver more visually pleasing results with much fewer artifacts and sharper edges.

To further demonstrate the robustness of our method, the visual comparison results on images from the Köhler [17] dataset are also provided in Figure 7. Again, it can be seen that artifacts and blurred edges in the zoom-in areas (see characters 'B', '70', and '15') are noticeable for these previous CNN based methods. Although results recovered by Kupyn [2] and Tao [14] are sharper than other methods, distortion still exists. We also tested the proposed DBCPeNet on some real-world blurred images from [45], and the results are shown in Figures 8 and 9. Since the kernel distribution and the kernel size between the GoPro dataset and the dataset from [45] are very different, the deblurring results by all the competing networks trained on the GoPro dataset contain visible artifacts and blurred edges (see the zoom-in areas). Compared with the other competing methods [1], [14], [2], [15], however, our method still reproduces sharper and more natural images. How to train a blind deblurring network with strong generalization capability remains an open problem that deserves further investigation.

C. Ablation Study

It is generally agreed that a larger scale training dataset which covers various image contents and blur models will bring benefit to train a robust deep network. The type of scenes and number of images in the current GoPro dataset, however, are barely sufficient to train an efficient network. Rather than

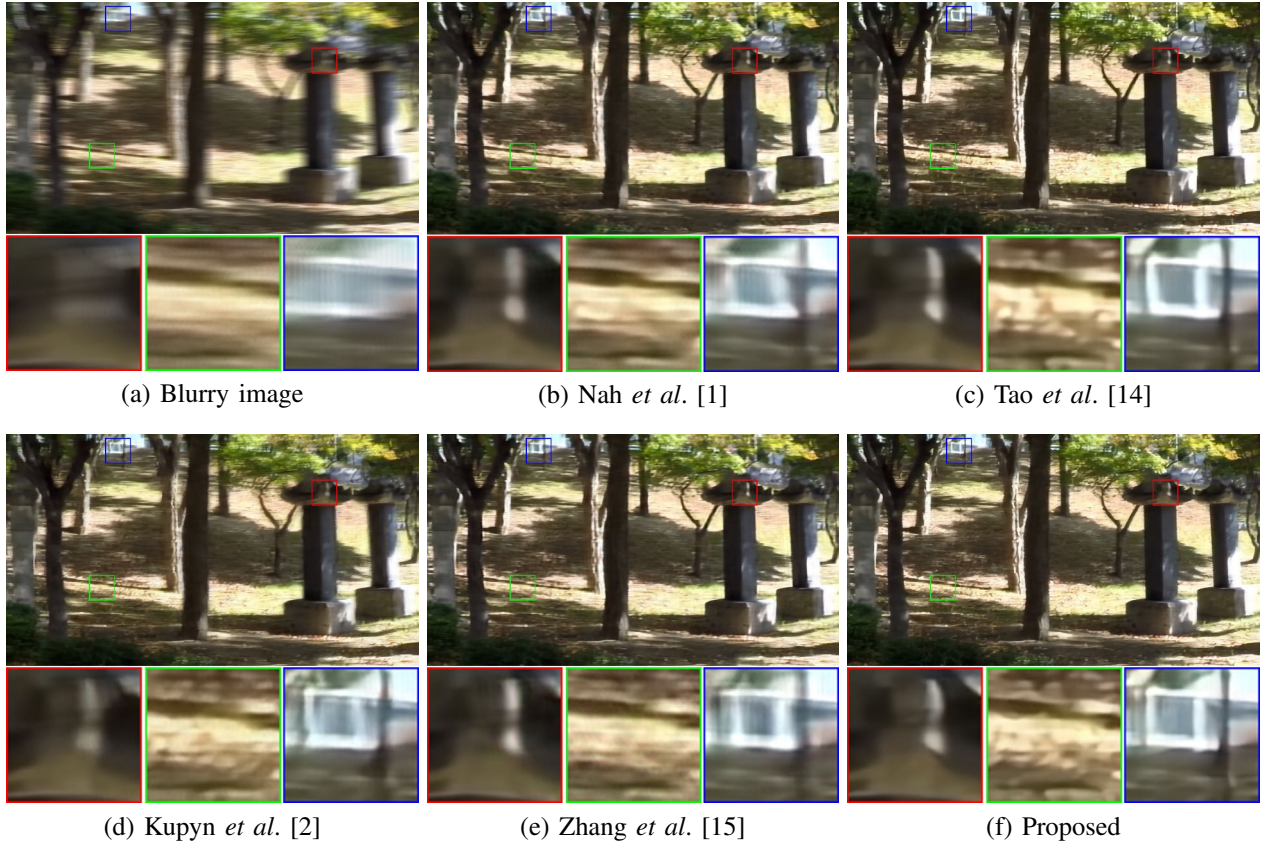


Fig. 4: Visual comparisons on a blurred image with high dynamic range. Image from the GoPro testing dataset [1].

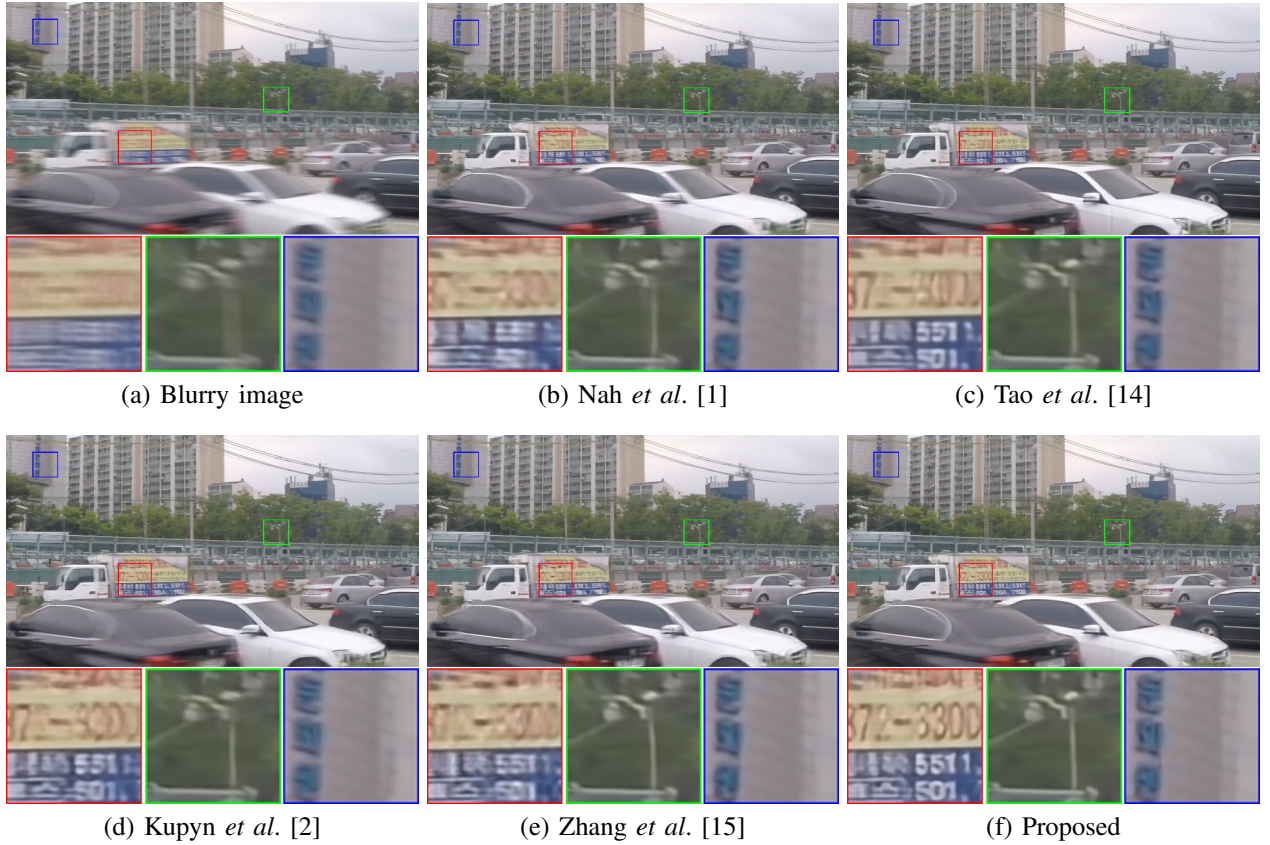


Fig. 5: Visual comparisons on a blurred image with large depth of field. Image from the GoPro testing dataset [1].

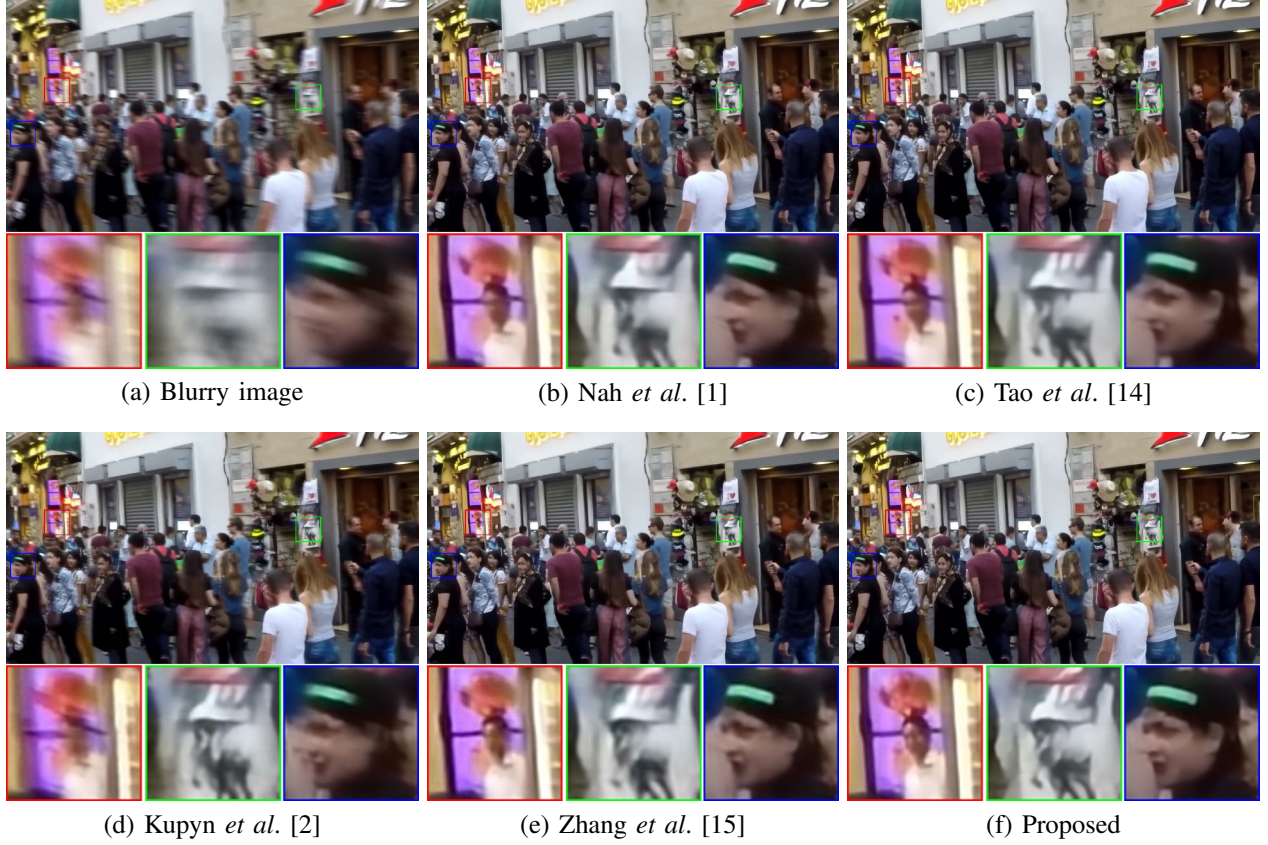


Fig. 6: Visual comparisons on a blurred image with moving objects. Image from the GoPro testing dataset [1].

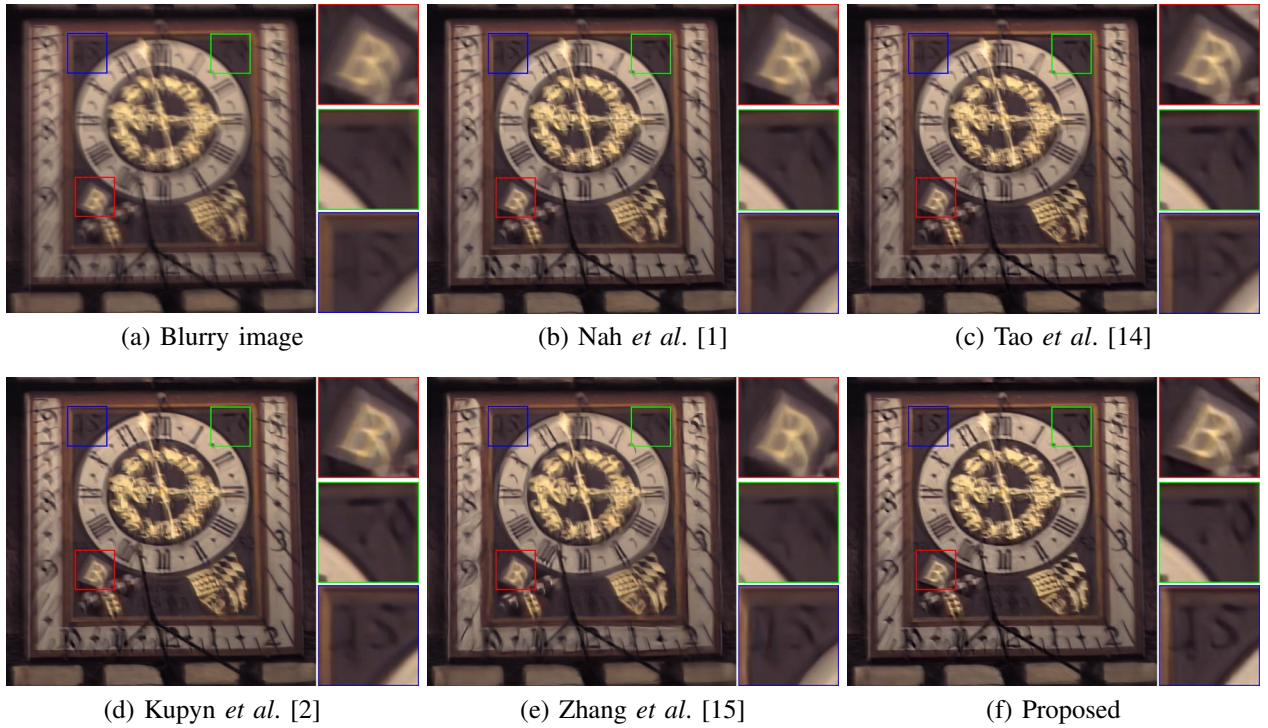


Fig. 7: Deblurring results on the Köhler dataset [17] by different methods.

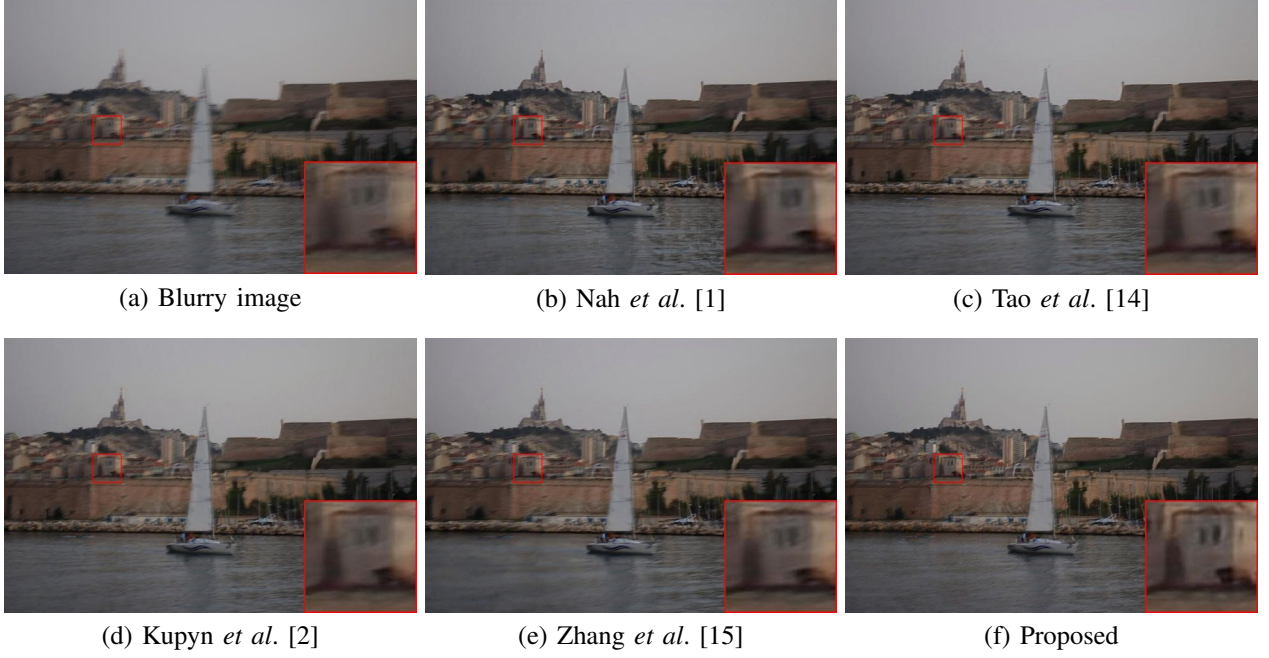


Fig. 8: Visual comparisons on a real-world blurred image with moving object. Image from [45].

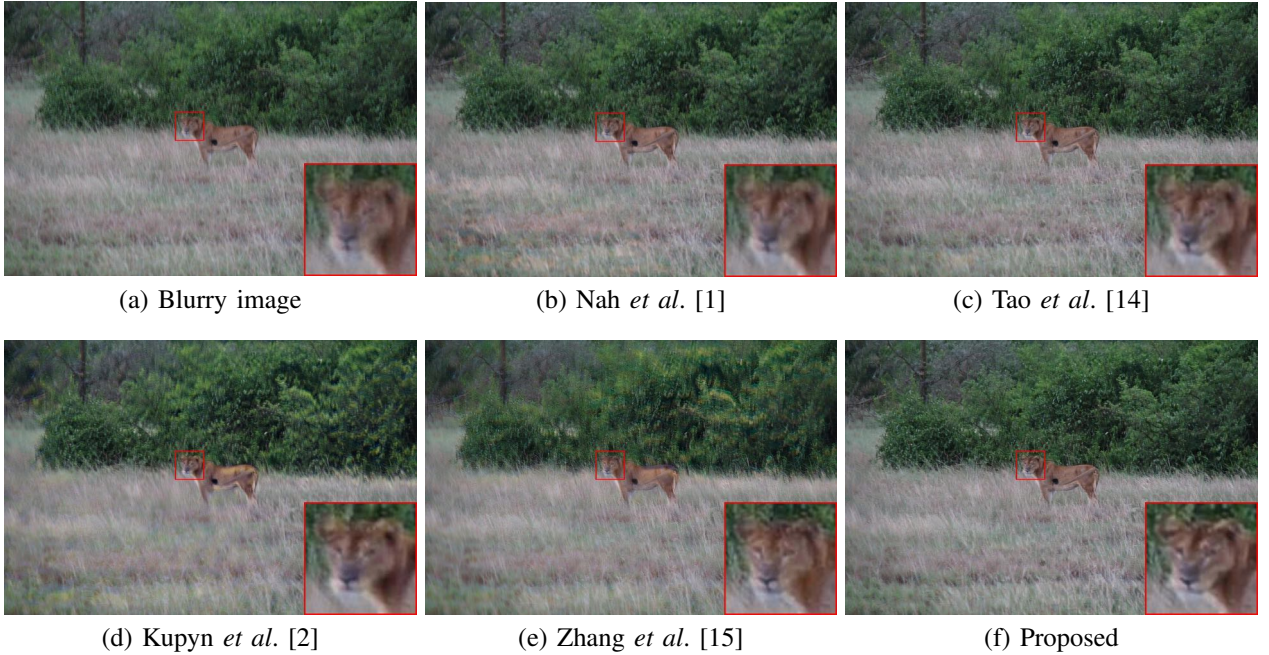


Fig. 9: Visual comparisons on a real-world blurred image with living animal. Image from [45].

enlarging the training dataset, we propose to integrate the dark and bright channels prior into CNN and exploit different scales of images for the performance improvement. In order to verify the effectiveness of the DBCPeL and IFSE structure, we conduct ablation studies to compare our proposed DBCPeNet with several baseline networks. Besides, the quantitative evaluation results of our DBCPeNet with different scale levels, different merge operations, and different regularization terms are also provided.

Evaluation of DBCPeL. As shown in Figure 3, the proposed

DBCPeL works in feature domain and is applied to both front and back layers. The reason of our network design is two-fold. (i) In the training phase, we have the ground-truth in the final layer (image domain) to supervise the model learning. Therefore, simply imposing DBCP on the final output images cannot achieve significant improvement. (ii) The hidden layers (feature domain) aim to convert the blurry image to sharp image step by step. Considering that the property of DBCP also exhibits in hidden layer features, enforcing DBCP and sparse constraints in hidden layers can make the learning of

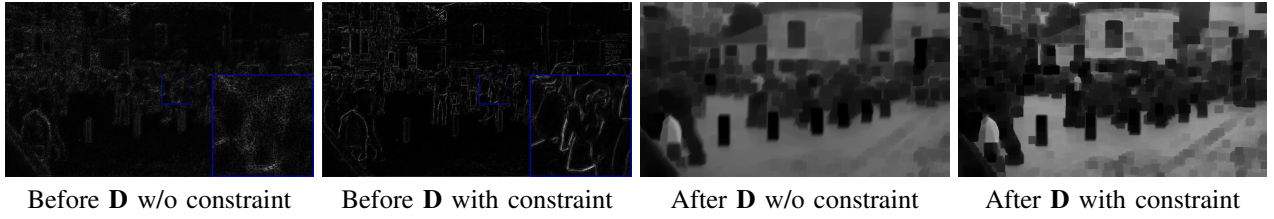


Fig. 10: One feature map before and after the dark channel extractor \mathbf{D} with and without DBCP and sparse constraints.

TABLE II: Ablation study on the dark and bright channels prior embedded layer (DBCPeL). The average PSNR (dB) on GoPro testing dataset is shown.

Method	PSNR
w/o DBCP	30.834
DBCP-final	30.891
DBCP-front	30.913
DBCP-front 2	30.917
DBCP-back	30.952
DBCP-back 2	30.955
DBCPeNet	31.102

early and deeper layers more effective.

We compare our DBCPeNet with 6 baseline networks, including w/o DBCP, DBCP-final, DBCP-front, DBCP-front 2, DBCP-back, and DBCP-back 2. Here ‘w/o DBCP’ refers to the model without using DBCPeL; ‘DBCP-final’ refers to the model applying DBCP and sparse constraint only to the final output image; ‘DBCP-front’ and ‘DBCP-front 2’ refer to the model employing one and two DBCPeL in the front parts of the network, respectively; and ‘DBCP-back’ and ‘DBCP-back 2’ refer to the model using one and two DBCPeL in the back parts of the network, respectively. All these 6 baseline networks share the same backbone as our DBCPeNet, except some of them take an additional convolutional layer to replace the DBCPeL. It is worth pointing out that all these 6 baseline networks use the proposed IFSE structure.

Table II shows the deblurring results. It can be seen that the one without DBCPeL performs much worse than the DBCPeNet in terms of PSNR (30.834 dB *v.s.* 31.102 dB). If we simply add DBCP and sparse constraints on the final output image, as done in previous DBCP based methods [11], [12], we can only get about 0.06 dB gain (see model DBCP-final in Table II). In contrast, placing the DBCPeL in the front or back part of the network could benefit dynamic scene deblurring (see models DBCP-front and DBCP-back in Table II). However, adding more than one DBCPeL in the front or back part of the network could not further boost the performance (see models DBCP-front 2 and DBCP-back 2 in Table II). This is mainly because the DBCPeL is introduced to guide the learning of hidden layers. Simply replacing DBCPeL in the same part of the network is not effective enough to learn the front or deeper layers. Thus, we place DBCPeL in both front and back layers and it achieves the best results.

To further verify the effectiveness of the proposed DBCPeL, we visualize the feature maps before and after the dark channel

TABLE III: Ablation study on the image full scale exploitation (IFSE). The average PSNR (dB) on GoPro testing dataset is shown.

IFSE	\times	\checkmark
PSNR	30.96	31.10

TABLE IV: Ablation study on the number of scales. The average PSNR (dB) index is listed for different scale level S on the benchmark datasets.

	$S = 1$	$S = 2$	$S = 3$	$S = 4$
GoPro	30.67	30.81	31.10	30.92
Köhler	25.53	26.28	26.79	26.94

extractor $D(\cdot)$ with and without DBCP and sparse constraints. In Figure 10, we randomly visualize one feature map before the extractor $D(\cdot)$ (with the $\text{abs}(\cdot)$ operator). We could found that the one with DBCP and sparse constraints has sharper edge and its dark channel is sparser.

Evaluation of IFSE. To demonstrate the advantages of our IFSE strategy, we compare DBCPeNet with a baseline multi-scale architecture which only works in the coarse-to-fine manner. Note that for a fair comparison, the baseline method shares the same backbone as our DBCPeNet and uses the same number of scales. Table III verifies our strategy. One can see that the one adopting the proposed IFSE structure (both coarse-to-fine and fine-to-coarse manners) can have 0.14 dB improvement in terms of PSNR index. These comparisons firmly indicate the proposed IFSE structure benefits performance improvement.

Number of Scales. We show the quantitative evaluation results of our method with different scale level S in terms of PSNR over the test data. In Table IV, one can notice that the multi-scale architecture can bring better results for dynamic scene deblurring. Our proposed DBCPeNet with $S = 3$ produces the best results for GoPro testing dataset. While for the Köhler dataset, the average PSNR index can be further improved with the increase of scale level S . In this work, we take the scale level $S = 3$ for both GoPro and Köhler dataset.

Evaluation of Merge Operations. To train the proposed DBCeNet, we take the ‘concatenation’ as the merge operation in both coarse-to-fine and fine-to-coarse training stages. To verify the advantages of ‘concatenation’, we compare it with several other merge operations, including addition, multiplication, and spatial transform [49]. Table V shows the quantitative

TABLE V: Ablation study on the different merge operations. The average PSNR (dB) on GoPro testing dataset is shown.

Operation	PSNR
Addition	30.76
Multiplication-final spatial transform [49]	30.72
Concatenation	31.10

TABLE VI: Ablation study on the different regularization terms. The average PSNR (dB) on GoPro testing dataset is shown.

	ℓ_1	ℓ_2	without constraint
PSNR	31.10	30.91	30.84

evaluation results of different merge operations in terms of PSNR on the GoPro test data. It is not a surprise that the operation ‘concatenation’ has higher PSNR scores than other merge operations since it combines feature representations without losing any information, resulting in better performance.

Evaluation of Regularization Terms. Since the dark and bright channels of a sharp image are sparser than those of a blurry image, the sparse constraint favors clear images over blurred images. To verify the advantages of ℓ_1 -regularization, Table VI compares the results of ℓ_1 -regularization with ℓ_2 -regularization and no constraint. One can see that ℓ_1 -regularization works the best.

V. CONCLUSION

In this work, we presented a simple yet effective Dark and Bright Channels Prior embedded Network (DBCPeNet) with a novel trainable dark and bright channels prior embedded layer (DBCPeL), which aims to integrate channel prior knowledge into a deep CNN for dynamic scene deblurring. By extracting the dark and bright channels of shallow features and enforcing sparsity on them, DBCPeNet can regularize the solution space of the network. Additionally, DBCPeNet works in both coarse-to-fine and fine-to-coarse manners to exploit information of blurred images at different resolutions to maximize information flow across scales. Benefiting from the dark and bright channels prior constraint and the effective multi-scale network architecture, the developed DBCPeNet outperforms previous dynamic scene deblurring networks by a large margin. Quantitative evaluations on the challenging GoPro dataset showed that the proposed DBCPeNet had at least 0.84 dB PSNR gains over the existing state-of-the-arts.

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