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Based LR Kernel Prior Model for Unsupervised Blind Super Resolution

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Abstract
The main challenge in Blind Super Resolution (BSR) lies in the unknown and diverse degradation models. Traditional methods often rely on paired low-resolution (LR) and high-resolution (HR) image samples for supervised training, which can be costly and difficult to obtain in real-world applications. To address this issue, we propose a Based LR Kernel Prior (BLKP) model for unsupervised kernel estimation and high-resolution image restoration.The BLKP model consists of two main components: the Pre-Trained Kernel Model (PTKM) and the Prior Kernel Estimation (PKE) module. PTKM employs a pre-trained neural network to estimate multiple potential blur kernels from LR images, providing kernel priors for the PKE module. The PKE module further refines the kernel estimation by integrating the PTKM-generated priors, observed LR images, and currently estimated HR images, optimizing the restoration process under dynamic degradation conditions.The proposed framework offers several key advantages. First, it eliminates the dependence on paired LR-HR samples, enabling unsupervised kernel estimation and image restoration, thus enhancing adaptability and flexibility in complex degradation scenarios. Second, its modular design allows seamless integration with existing image restoration models, providing an efficient and scalable solution for BSR tasks. Experimental results demonstrate that BLKP delivers superior restoration performance across various blur kernel environments, highlighting its potential and value in real-world applications.

Keywords: *Blind Super-Resolution, Kernel Prior.*

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I. INTRODUCTION

Deep learning provides a promising approach to addressing the Blind Super-Resolution (BSR) problem, where the goal is to reconstruct a high-resolution (HR) image from a low-resolution (LR) observation with an unknown blur kernel. This process is inherently non-convex and ill-posed, making it highly challenging. To tackle this, most learning-based methods adopt a supervised learning framework that leverages paired LR-HR samples and prior image knowledge to alleviate non-convexity and ill-posedness. However, these methods face significant limitations due to their reliance on pre-defined labeled datasets.First, acquiring high-quality paired LR-HR samples is both costly and time-consuming. Second, in certain applications such as fast-moving targets (e.g., satellites or airplanes) or medical imaging (e.g., cardiac motion), obtaining paired data is nearly impossible. This motivates the search for methods that bypass the need for labeled training data.

Existing BSR methods fall into two major categories: explicit degradation strategies (typically supervised) and implicit degradation strategies (often unsupervised). Explicit Degradation Methods: These methods rely on explicitly designed constraints or prior knowledge to model the degradation process. They apply prior assumptions, such as blur kernel models or noise models, to restore HR images. While effective for known degradation models, their reliance on predefined priors limits their adaptability to complex, unknown, or varying degradation processes. Implicit Degradation Methods: These methods train end-to-end deep learning networks to learn the degradation process from data. They avoid explicit physical models by learning data-driven priors from large-scale paired samples. Although effective, they suffer from limited generalization to new blur kernels or unknown degradation scenarios. They also require extensive paired data and high computational resources, limiting their scalability.

To overcome these challenges, we propose a novel unsupervised BSR method called the Based LR Kernel Prior (BLKP) model. BLKP estimates blur kernels and restores HR images without paired LR-HR samples, making it practical for real-world applications. We use a pre-trained neural network to estimate multiple potential blur kernels from LR images. These kernels serve as prior inputs for further refinement. PKE adjusts and optimizes the blur kernel estimation based on the PTKM-generated kernel priors, the observed LR image, and the current HR estimate from the Image Restoration (IR) model. This dynamic process refines the kernel estimation adaptively during restoration.

The main contributions are summarized as follows:

1. The BLKP model proposed in this paper eliminates the dependence on paired samples by generating kernel priors and dynamically estimating fuzzy kernels, achieving unsupervised kernel estimation and image restoration. This feature of not requiring paired training data significantly improves the applicability of the model in practical scenarios, especially when paired data is difficult to obtain, which is of great value.
2. The core innovation of BLKP model lies in its modular design, especially PTKM and PKE. PTKM generates multiple possible estimated blur kernels from low resolution images through a simple pre trained network, providing initial conditions for subsequent kernel estimation. The PKE module further combines observed low resolution images with restored high-resolution images to optimize and adjust the blur kernel. This modular design enables the BLKP model to serve as a universal kernel estimation tool, easily embedding into existing image restoration models, providing great flexibility and scalability.

II. METHOD

2.1 Overview

The degradation model for blind super-resolution can be mathematically expressed as:

$$y = (\, x \otimes k \,)_{\downarrow_s} + n \tag{1}$$

where y represents the LR image, x represents the HR image, $\otimes$ denotes the convolution operation, k is the blur kernel, $\downarrow_s$ is the downsampling operation with a scaling factor s, and n is noise. The BSR problem can be formulated as a Maximum a Posteriori (MAP) problem:

$$\max_{x,k} p(y|x,k)p(x)p(k) \tag{2}$$

where $p(y|x,k)$ represents the likelihood of the observed LR image y, and $p(x)$ and $p(k)$ are the priors for the HR image and the blur kernel, respectively. The image prior $p(x)$ has been extensively studied and designed over the past decade, typically using deep learning or other content-based models to capture the structure and patterns of images. In contrast, the study of blur kernel priors $p(k)$ has only recently gained attention. Due to the relatively low cost of obtaining blur kernel samples and the efficiency of their training phase, the study of blur kernels has become a popular direction in blind super-resolution tasks.

we propose BLKP model consisting of PTKM and PKE. In this model, the PTKM module is responsible for generating preliminary kernel priors, while the PKE module uses these priors from PTKM to further estimate the blur kernel. Let t= t = 1、2…T represent the number of iterations between these two modules, where in each iteration, the estimated blur kernel k^t and the high-resolution image x^t represent the outputs of the t-th iteration.

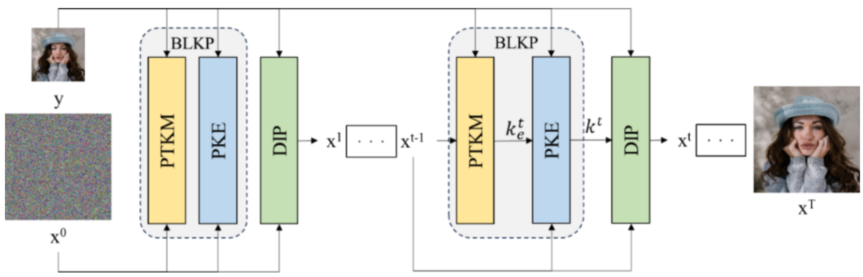

Figure 1: Overview of BLKP-DIP Method

Through this alternating iteration method, the BLKP model is able to estimate the blur kernel based on the latest HR and LR images in each iteration, and gradually restore high-resolution images. This method fully utilizes the information in LR images to generate kernel priors, while optimizing the blur kernel in the absence of paired data, effectively solving the problem of blind super-resolution.

2.2 Based LR Kernel Prior

The main function of the BLKP model is to dynamically estimate the blur kernel in each iteration by combining the content information of the latest HR image and the initial LR image. This process not only effectively captures the features of image blur, but also provides accurate blur kernel prediction in image restoration tasks, in order to further restore clearer images. The BLKP model consists of two key modules: PTKM and PKE. These two modules work together in the iterative training of the model to optimize the prediction process of the fuzzy kernel.

Specifically, the PTKM module is mainly responsible for providing preliminary blur kernel estimation based on LR images. This module relies on a pre trained deep neural network, which learns the relationship between blur kernels and image content by pre training on a large number of images, thus providing a preliminary blur kernel estimate for each low resolution image. Due to the fact that image blurring is a degradation process, the initial estimation value of PTKM's output blur kernel may not be completely accurate, but it provides a reasonable starting point for subsequent blur kernel optimization. In the subsequent training process of the model, PTKM will fine tune based on the output results of the PKE module to improve the accuracy of prediction. The PKE module is based on a flow based kernel prior model, which optimizes by constraining the fuzzy kernel prior. PKE optimizes based on the fuzzy kernel estimation provided by PTKM and the degraded image results of this iteration in each iteration. PKE integrates this information and continuously adjusts the fuzzy kernel estimation values to better match the fuzzy features in the actual image degradation process. Specifically, PKE introduces prior knowledge and physical constraints of the kernel during the optimization process to ensure that the estimated fuzzy kernel has a more reasonable physical interpretation, avoiding unreasonable fuzzy kernel estimation and improving the stability and robustness of the entire model.

The overall process of the PTKM is as follows: First, the low-resolution image y and the high-resolution image from the previous iteration x^{t-1} are input into the model. These are processed through the kernel model to obtain an initial estimate of the blur kernel k'. Specifically, this paper introduces an output module that can generate multiple initial blur kernel estimates, such as k_1', k_2', k_3' etc.Next, the process enters the weight calculation module. The initial blur kernels k_1', k_2', k_3' are convolved with the high-resolution image x^{t-1} from the previous iteration to generate multiple predicted low-resolution images. These predicted images are compared with the actual low-resolution image y, and the error is calculated. Based on this error, a weight map is generated. This weight map is used to adjust the blur kernels, and ultimately, the initial blur kernels are fused through a weighted combination to obtain the optimized blur kernel k_e.

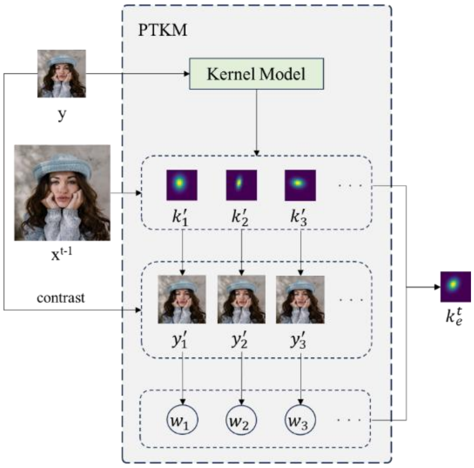

Figure 2: Overview of PTKM

The Kernel Model mainly consists of two steps: First, feature extraction: by using the ResBlock module of MAConv to extract features from low resolution images, learning the fuzzy patterns and relationships between channels in the image. Second, fuzzy kernel reconstruction: based on the extracted features, a preliminary fuzzy kernel estimation is constructed to provide initial conditions for subsequent fuzzy kernel optimization. The detailed workflow and structure of this module are shown in Figure 3, with a focus on how to extract effective fuzzy features through the ResBlock module using MAConv, and reconstruct the fuzzy kernel based on these features. Specifically, in the final Reshape, this article not only outputs one fuzzy kernel to increase the likelihood of observing excellent fuzzy kernels.

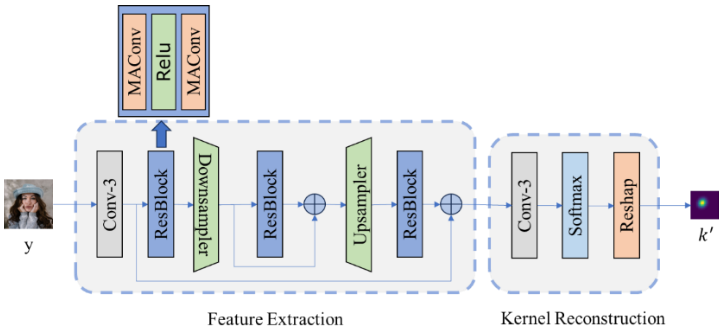

Figure 3: Specific model diagram of Kernel Model

2.3 Prior Kernel Estimation

In the PKE model, the estimation of the blur kernel relies on a lightweight network G_k based on flows, which learns and optimizes the prediction of the blur kernel through its parameters Φ_k. Specifically, the network's output at the ttt-th iteration is given by:

$$k^t = G_k(\Phi_k^t) \tag{3}$$

where G_k is a lightweight network, Φ_k^t represents the optimized parameters at the t-th iteration, and k^t is the output blur kernel. The initial input to the network G_k is random noise, allowing the network to start from a random initialization and gradually converge to the correct blur kernel estimate through learning and iterative optimization.To ensure the accuracy of the estimation, the network incorporates two key consistency checks during the optimization process: data consistency check and blur kernel consistency check. These checks help refine the estimated blur kernel and ensure its validity at each iteration.

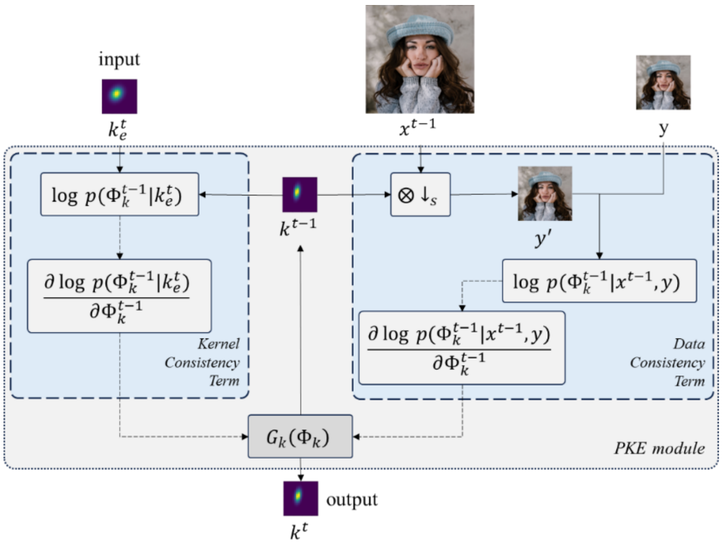

Figure 3: Specific model diagram of PKE

2.4 Depth image prior model

DIP[1] is a deep learning method for image restoration that captures low-level image statistical features. It begins with a fixed random noise input and estimates the HR image. Unlike traditional deep learning methods that typically rely on large-scale pre-trained datasets, the core advantage of the DIP method is that it does not require any pre-existing training data. Instead, it only depends on the image to be restored for performing the restoration task. This enables DIP to efficiently and quickly restore images, even when data is limited.

The DIP method optimizes the network parameters Φ_x progressively so that the generated image matches the target image under a specific metric. During the restoration process, the network learns both low-level and high-level features of the image, including texture, structure, edges, and other visual information. By continuously optimizing its parameters, the network generates a high-resolution image that gradually aligns with the features of the target image. In this process, the network not only captures local image features but also models the global structure of the image, achieving high-quality image restoration.

III. EXPERIMENTS

It was observed that the rerun column bottom stream temperature has greater effect on the linear alkylbenzene yield than the temperature variation of the top stream. At higher temperature of both streams , lower percentage yield of average wt. % of linear alkylbenzene was obtained with that of the top stream being the lowest at 87.5% as against 93.3% for the bottom stream. The highest linear alkylbenzene yield of 99.4%was recorded at bottom stream temperature of 280°C and pressure of 115Kpa.

Based on the widely adopted kernel assumption, we conducted experiments on anisotropic Gaussian kernels, as shown in Figure 4. The kernel size was set to $(4s + 3) \times (4s + 3)$. For the Gaussian kernel, the width range was set to [0.175s,2.5s], the rotation angle range was set to [0,π], and the scale factor was s=4. We synthesized LR images with random kernels using Equation 4.1 for testing on five popular public benchmark datasets, including Set5 [4], Set14 [52], BSD100 [30]. We compared these kernels based on Peak Signal-to-Noise Ratio (PSNR) and evaluated the HR images based on both PSNR and Structural Similarity Index (SSIM) [2].

Table 1 Comparison with advanced algorithms on various datasets (PSNR/SSIM) (bolded for optimal results)

	Set5	Set14	BSD100
Double-DIP[3]	20.99/0.5578	18.31/0.4426	18.57/0.3815
DASR[4]	27.37/0.7859	25.43/0.6591	25.11/0.6129
DIP-FKP[5]	27.77/0.7914	25.65/0.6764	25.15/0.6354
BSRDM[6]	27.81/0.8029	25.35/0.6859	25.61/0.6526
DCLS[7]	27.50/0.7948	25.68/0.6639	25.34/0.6169
DiffBIR[8]	25.15/0.6468	23.01/0.5935	23.88/0.5586
DARM[9]	26.25/0.6818	24.19/0.6187	24.29/0.5898
DIP-DKP[10]	28.03/0.8039	25.98/0.6878	25.66/**0.6531**
DIP-BLKP	**29.22/0.8337**	**26.11/0.6936**	**25.75**/0.6446

From Table 1, it can be seen that DIP-BLKP is the most outstanding super-resolution method in the table, with PSNR and SSIM of 29.22/0.8337, 26.11/0.6936, and 25.75/0.6446 on Set5, Set14, and BSD100 datasets, respectively, ranking first, demonstrating significant advantages on various datasets. Specifically, in the Set5 dataset, DIP-BLKP achieved the highest values in both PSNR and SSIM metrics, indicating its excellent ability to restore details and maintain structure in small-scale, high-quality image restoration tasks. In the more complex Set14 dataset, DIP-BLKP still outperforms other methods with a performance of 26.11/0.6936, and even with a wider variety of image types, it can accurately restore high-resolution images. In the most challenging BSD100 dataset, DIP-BLKP also performed well, with PSNR and SSIM metrics of 25.75 and 0.6446, respectively. Only the SSIM metric performed slightly worse, indicating that its generalization ability and robustness in complex scenarios are in a leading position.

When compared with other methods, the advantages of DIP-BLKP are more pronounced. Compared with traditional methods such as Double DIP and DASR, it has significantly improved both PSNR and SSIM metrics, especially on the complex dataset BSD100, with PSNR improvement exceeding 7.18 and SSIM improvement of about 0.2631, demonstrating its significantly improved reconstruction ability. Compared with its closer competitor DIP-DKP, DIP-BLKP also performs better, with a 1.19 increase in PSNR on the Set5 dataset and a 0.006 increase in SSIM on the Set14 dataset, indicating further optimization of its model capabilities under the same framework. At the same time, DIP-BLKP can not only restore high-quality image details, but also maintain the overall structural consistency of the image well, avoiding problems of excessive smoothness or texture loss.

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