A Comparative Study of Kernel Basis Network (KBNet) for Advancing Image Restoration and Denoising

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Abstract

This paper presents a comprehensive comparative study of Kernel Basis Network (KBNet) for enhancing image restoration and denoising processes. Traditional methods for image restoration often face challenges in handling complex noise patterns and preserving fine image details. In this study, we explore the efficacy of KBNet, a novel deep learning architecture inspired by kernel basis techniques, in addressing these challenges. Through a series of experiments and comparisons with state-of-the-art methods, we demonstrate the superior performance of KBNet in restoring images corrupted by various types of noise, while preserving important structural details. Our findings underscore the effectiveness of KBNet as a promising approach for advancing image restoration and denoising tasks.

Keywords: Kernel Basis Network, Image Restoration, Image de-noising, Comparison.

1. Introduction

One use of image processing is the enhancement of raw images captured by various sensors attached to various artifacts. Consequently, the processed image is of better quality than the one that was felt initially. Image representation, pre-processing, enhancement, restoration, analysis, construction, and compression are some of the essential phases in image processing. In addition to restoring, enhancing, and filtering images, digital image processing also analyzes and restores them and extracts features from them.

Image restoration, which uses several predefined standards to achieve specific upgrades on each image, is an integral aspect of processing. Furthermore, constructing or reconstructing an image from numerous old, deteriorating image data is usually the primary objective of image restoration. The restoration process also carries out specific tasks, such as using the de-blurring function to remove blur from an image. Two model, the spatial and frequency domain models are used to analyze the images used in the image restoration process. Furthermore, the probabilistic model of image degradation is the primary basis for image restoration. According to Azim et al. (2022) [1], the image restoration model produces images with improved appearance and minimal blur. Generally speaking, noisy and blurry images which do not accurately represent the desired target are one of the degradation sources that impact imaging systems.

For this reason, image restoration is a crucial step in recovering usable images for a variety of uses, including astronomy, medical diagnosis, remote sensing, and surveillance [2]. Digital image processing is used in many everyday applications, such as digital cameras, intelligent/smart traffic monitoring, digital signature validation, and hand- writing recognition on checks. However, due to a few inevitable sources, the input image is tainted by a variety of noises. Transmission errors, insufficient equipment, subpar image sensors, problems with image acquisition, and interference from natural phenomena are the main causes of noises. As such, it becomes crucial to recognize and remove any noise present in an image. In addition, the purpose of developing the denoising approach was to preserve visual information while removing noise (Njima, et al., 2022). The image deblurring procedure is also used to produce a clear and functional image. The two main and most important areas of the digital image processing process these days are image restoration and deblurring techniques [3].

1.1 Image Denoising

1.1 Image Denoising Digital images are becoming more and more important tasks for common applications in daily life. Nonetheless, noise typically affects the image captured by a sensor. The digital image is more susceptible to noise, which has a significant impact on the image quality. Therefore, by removing superfluous noise from the input image, image denoising is used to restore the actual image information. Visual artifacts, noise, and the influence of visual quality are the key indicators of image quality. Furthermore, by taking into account specific parameters using the important factors, denoising techniques are developed. Furthermore, it is recommended to optimize the aforementioned parameters in order to achieve a higher-quality final restored image (Azim, et al., 2022) [4].

Image denoising is a well-known method for improving image quality in image processing. It removes noise from noisy input images while preserving the quality of the original image. Typically, during the image transmission and acquisition process, the actual data in the input is impacted or deteriorated. To improve anatomical information that is suppressed by noise, denoising is a crucial step in the medical imaging process. Conventional denoising methods, including wavelet soft thresholding, median filter, and wiener filter, are applied to noisy input images to enhance image quality. Norbert Wiener invented the Wiener filter, which uses a random process to compute statistical estimation of an unknown signal in order to reduce Mean Square Error (MSE). In addition, the dynamic and linear nature of the Weiner filter allows for point estimation despite its limitations in eliminating multiplicative noise (Azim, et al., 2022)[5].

In conjunction with non-linear image processing applications, edge-preserving dig- ital filtering models like the median filter are usually used to eliminate noise from images. On the other hand, the median filter's significant computational cost is its main drawback. When it comes to picture denoising, the wavelet transform is an essential tool. The usage of wavelet transform, which is advantageous for localization in both the frequency and space domains, is also included. Flexible execution in specific two-dimensional signals is usually made possible using wavelet packets. While there are a number of approaches to the problem of denoising noisy images, each of them has its own unique set of difficulties. Traditional methods often de-noise the whole picture despite the fact that these models failed to distinguish between low- and high-frequency components due to the rapid image changes. Filtering out high- frequency models while keeping low-frequency components helps in denoising (Azim, et al., 2022)[5].

The technique of image denoising is used to remove noise from noisy input images. Curves, densities, images, and other infinite-dimensional objects can be recovered using the wavelet technique. Because wavelet techniques can capture signal energy in a range of energy transform values, they are more effective at eliminating noise. In a wavelet field, the wavelet coefficient reduction process is typically employed by wavelet- based methods. Denoising is the first step in the image processing process and is more important. Furthermore, in order to effectively remove the corrupted data, denoising must be applied. When compared to a noisy image, image denoising is clearly used to improve image quality. Noise reduction is regarded as the first step in image processing, despite being a crucial approach. Image denoising eliminates preservative noise while preserving crucial signal properties. Additionally, the following is an explanation of the image denoising process. The input image is first moved to multiple domains in order to identify the noise element. The thresholding operation is used to remove noise after the noise element has been identified. An image free of noise is produced once the noises have been removed. Image denoising is currently a very desirable area of study. The median filter is one of the conventional non-linear filters used to de-noise an image (Bazzi, and Chafii, 2023). The median filter typically relies on a local analysis of the moving window's pixels [6].

One can observe the primary importance of image denoising in low-level vision from various angles. First of all, noise corruption in image sensing is inevitable and can severely impair the visual quality of the resulting image. Second, a number of image processing and computer v1s10n tasks require the fundamental step of eliminating noise from the acquired image. In the end, various image restoration problems are resolved by using variable splitting models to solve sense m unrolled interference one after the other. Both model-based and discriminative learning-based approaches exist for picture denoising at the present moment. Despite their flaws, model-based methods such as WNNM and Block-Matching and 3D filtering (BM3D) are versatile enough to deal with denoising problems involving varying degrees of noise. For example, optimisation methods are typically laborious and cannot be used directly to remove spatially variant noise. Furthermore, handcrafted image priors such as non local self and sparsity similarity are frequently used in model-based approaches, but they are not very effective in describing complex image structures (Bazzi, and Chafii, 2022) [7].

One classic inverse problem in the low image processing domain is image denoising. One of the main causes during image acquisition and transmission is an inadequate photography environment or n01sy transmission channel. To guarantee accurate understanding of the image's content, many denoising methods are employed to eliminate noise and restore the original data from a damaged image. So, picture denoising methods improve the performance of image processing models for object detection and edge recognition. Furthermore, in a picture polluted with Gaussian noise, every pixel has a value added to it according to the zero mean distribution. On the other hand, when impulsive noise degrades the picture, it merely replaces some of the pixels while leaving the rest of them unaltered [8].

Impulse noise may be categorized into two types: random-valued and fixed-value. The distribution of noise values determines the former. The denoising procedure is also simplified because there is just one kind of noise in a picture. Still, most approaches aim to eliminate impulse and noise that follows a normal distribution. The denoising challenges are more complex since each image is affected by a distinct noise probability distribution when it comes to Gaussian impulse noise. Getting rid of denoising issues, nevertheless, is more important for a clean image (Bazzi, and Meilhac, 2022) [9].

One of the fundamental problems in computer vision and image processing is image denoising. Generally speaking, noise is a random signal that deteriorates the image while it is being acquired. The majority of effective techniques are designed to extract the true image from a noisy image. For image denoising, there are typically two types of methods available: non-linear models and linear models. Although they can't stop image texture and edge information, linear techniques like the wiener and gaussian filters are used to reduce noise in flat image areas. Non-linear techniques are utilised to solve these restrictions because they have a higher capacity for preserving edges than linear techniques. Furthermore, a number of studies in various fields related to image denoising and texture enhancement have also developed fractional calculus (FC) (Bazzi, and Chafii, 2023) [10].

A common problem in digital image processing, image denoising is a basic problem in the image restoration process. Here, segmentation, classification, and identification are the processes and analysis that come after noise reduction as a crucial pre-processing step to obtain more accurate information from the image. Further- more, there is a trade-off between noise reduction and feature preservation due to the complexity of image denoising. A vast array of image denoising techniques, such as methods based on low rank, total variation, and non-local self-similarity, have been introduced recently. Nowadays, the most widely used methods are the Rudin, Osher, and Fatemi (ROF) approaches, which vary the pixel level to reduce the overall variation of the image. In the meantime, the gradient model of the ROF approach is created as an apparatus to be a staircase artefact with fine structure, using the Laplacian distribution for image denoising (Gopatoti, et al., 2022) [11].

Because video and image communication are so important in daily life, higher quality images are required for better image analysis and comprehension. Generally speaking, image acquisition devices are used to take digital images. However, because they are made up of a variety of sensors, image acquisition devices are more susceptible to noise. As a result, the detected noise level is taken into account during the picture taking procedure. For this reason, the image denoising technique is necessary to improve the visual quality of images [12]. Image denoising is frequently used to reduce unwanted noise and preserve important information, such as edges and texture. Various types of noise can be introduced into a picture, such as thermal noise, multiplicative noise, additive white gaussian noise (AWGN), salt and pepper noise, and others. In recent decades, a number of methods for image denoising have been introduced. For the purpose of image denoising, the performance parameters primarily depend on edge detection, multi-resolution, and sparsity. As a result of energy compaction, the fundamental transform domain approach is developed, and the image is represented using multiple dominant coefficients. Additionally, thresholding of transformed coefficients can be used to reduce the noise effects. Lastly, a denoising image is extracted using the transform analysis's modified coefficients. Furthermore, a number of conventional techniques are developed for image denoising, such as wavelets, contourlets, curvelets, Discrete Cosine Transform (DCT), and shearlets (Wang, et al., 2021)[13].

In medical image analysis, the denoising process is a more important pre-processing model. In addition, the denoising process is required in order to analyze the data. Furthermore, physicians and radiologists also use image processing to identify diseases [14].

Generally speaking, noises taint the best medical pictures. Degradation includes things like suppressing sand edges, blurring boundaries, and structural information. Additionally, a variety of strategies are developed to limit the noise. Finding important features, like edges and boundaries, is the main goal of the denoising process (Gopatoti, Vijayalakshmi, 2022). The filtering process, which is divided into two types: linear and non-linear filters, is used to execute image denoising. The mean filter and gaussian filtering are also important illustrations of the spatial denoising technique. However, because they obfuscate sharp edges and break lines, it is unclear how well linear filters perform; as a result, non-linear filtering is used [15].

Furthermore, the three main requirements for creating an efficient filter are minimum area, low power, and high speed. A filter with the shortest evaluation time is preferable to one with the longest evaluation time. Furthermore, non-local means filters, shrinkage techniques, total variation, and various transforms are included in traditional noise removal methods. In addition, wave atom, curvelet, and wavelet model transforms are used in the noise removal process (Gopatoti, et al., 2018) [16].

Blurring is a common structure of ideal image bandwidth reduction brought on by an imperfect image generation process. Furthermore, the relative motion of the cam- era and the original scene can cause blurring (Gopatoti, Ramadass, 2017). Blurs are typically caused by atmospheric turbulence, optical network aberrations, and relative motion between the camera and the ground. Aside from blurring effects, noise is one of the main causes of recorded image degradation. On the other hand, noise can be created using an image and acquisition medium [17].

1.2 Need for Image Denoising

Several factors point to the image denoising model's major importance in low-level vision. First of all, noise corruption in image sensing is inevitable and can seriously impair the visual quality of the resulting image. In many computer vision and image processing models, removing noise from the original image is an essential step. Second, the best test to assess image prior techniques and optimisation algorithms from Bayesian perception is image denoising (Raviteja, et al., 2019)[18].

1.3 Image Restoration

In numerous fields, such as thermal analysis, agricultural building, remote sensing, graphic design, and medical imaging, image restoration is the most important task. Plans for image restoration that aims to recover high-quality images from noisy, degraded images. According to Godavarthi, et al. (2018), the degradation process is typically described using a linear transformation in the image restoration process [19]. Different signal processing system algorithms are used to recover the degraded images. Based on non-local methods, the clean patches are independently found or work in tandem with other comparable patches. As a result, the positions of estimated patches in images are determined, while the average of overlapped patches is used to obtain the reconstructed image. Furthermore, during the image denoising process, overlap- ping images are first broken down and each patch is individually denoised. Lastly, the simple averaging model is used to obtain the denoising image (Gopatoti, et. al., 2018). For many crucial uses, including surveillance, medical imaging, remote sensing, low-level image processing, and so on, image restoration usually seeks to restore a high-quality picture from a low-quality original [20].

Denoising techniques are applied to corrupted images as part of the image restoration process, which creates unique images. Denoising is done prior to the restoration process in order to remove noise, as the restoration model largely enlarges the noises. Researchers continue to find image denoising models challenging because of the blur- ring, artifacts, and residual noise that arise during the noise removal process. One of the biggest obstacles, though, is controlling the staircase effect while keeping the image sharp and convex. In order to get around the limitations of denoising, researchers are primarily working on creating methods that preserve edges and smoothness (Deepak, et al., 2023) [11].

In the field of image processing, image restoration models are extensively used in a variety of applications, including medical imaging, materials science, astronomical imaging, and remote sensing. Pre- and post-processing of images are typically done during the image restoration process. These days, digital images play a major part in a number of fields, such as geographic information systems, satellite television, and astronomy. Because images are susceptible to different types of noise, their quality is generally distorted. By preserving edge information, the image restoration process is used to remove noise from corrupted images. Despite destroying the image's edge information, noise smoothing techniques magnify unwanted noises (Sriram, et. al., 2022) [21].

One popular method for calculating uncorrupted images from noisy or blurry images is image restoration. In addition, image restoration is a fundamental task in image processing that finds application in the lower echelons of computer vision and video processing. Furthermore, image restoration is primarily used in security and surveillance, medical, and computer vision models for image generation. Addition- ally, the unchangeable image degradation process that produces an ill-posed inverse process makes image restoration more difficult. As a result, a number of strategies, including model and learning-based approaches, are created to address the problems with image restoration. Nowadays, deep neural networks (DNNs) are primarily used, and they have shown superior performance in various image restoration tasks, such as reducing image compression, achieving super resolution, de-blurring, and denoising images (Upadhyay, et . al., 2022)[22].

Removing or minimizing degradations introduced during the image acquisition process is the main goal of image restoration. For example, noise, pixel value errors, motion blur, and out-of-focus blur based on predefined degradation phenomenon information. According to Sadhana, et al. (2022), this model addresses the degradation process and uses an inverse process to regenerate the image. Long-range image acquisition is never easy due to the possibility of atmospheric turbulence degradation. Due to variations in refractive index caused by air particle density, turbulent air flow, temperature changes, humidity, and carbon dioxide level, the captured image is distorted and blurry. As a result, these variations significantly deteriorate the quality of images and the effectiveness of different computer vision tasks, such as object detection, tracking, and recognition [23].

The process of restoring images, also known as de-convolution and de-blurring, involves estimating or reconstructing a clear image from a noisy or blurry one. In essence, it aims to perform operations on an image, which is the opposite of an image-forming system's imperfection (Rajender, et al., 2022) [24]. When using image restoration techniques, it is assumed that the fundamentals of the degradation system and noises are known beforehand. In a practical state, however, the prior information cannot be directly obtained from the image generation process. Blur identification's primary goal is to pinpoint the characteristics of a flawed imaging system from an observed deteriorated image to a successful restoration procedure (Gopatoti, 2022) [25].

1.4 Optimization Techniques and Applications

In recent days, various pre-processing restoration approaches are developed for achieving optimal results. The restoration techniques are widely classified into three types, such as spatial and spectral methods, filter-based or morphology approaches as well as Sparse Representation and Low-Rank (SR-LR)-based models. Moreover, the non-local approaches are executed using the intrinsic similarities available in image patches. This process directs to enhance the development of several non-local image restoration techniques used in. In addition, a non-local restoration process is utilized in many research works in order to group similar patches in image. In general, sparse representations are attained using the sparsity techniques. Gaussian Mixture Models (GMM) is used in various signal processing methods, such as audio processing, video applications, image denoising and image segmentation. Expected Patch Log Likelihood (EPLL) is devel- oped for weight initialization, however devising a global approach for the whole image is very inflexible due to dimensionality curse. Therefore, different image restoration techniques have been developed in recent days to address modeling with patch priors (Nalajala, et al., 2018) [26].

In recent days, Deep Neural Network (DNN)-based approaches are widely developed for image denoising processes, because of inspiring performance rather than model-based techniques. The effectual denoising approach, termed DCNN, was developed by employing batch normalization models and residual learning techniques. In addition, an improved fully convolutional encoder decoder network was introduced for image denoising process through symmetric skip connections. Moreover, Generative Adversarial Network (GAN) is introduced for modeling noise distribution over noisy input images, and then integrated clean images in order to create paired samples for the training process. The non-local operations are integrated with CNN techniques to exploit non local properties of image features image restoration approach is generally categorized into two kinds based on degradation knowledge. The deterministic model is applied, while prior knowledge about degradation is known, whereas stochastic technique is employed, when prior knowledge about degradation is unfamiliar (Ahmed, et al., 2018) [2][11].

1.5 Applications of image restoration and denoising

The process of image denoising and restoration is widely used in daily life for a variety of purposes, some of which are described below.

- The first and most important step in astronomical applications is the image restoration process, which removes Poisson and Gaussian noise from astrological images.
- The super resolution method is very useful for medical imaging applications like MRI and computerized tomography (CT). Even with low resolution, the surgeon may still acquire several pictures, which aids in the execution of meticulous, targeted surgery.
- To improve the resolution of the acquired satellite image, multispectral image restoration 1s was carried out.
- The resolution of mobile cameras is also increased through the use of image restoration techniques.
- To improve video resolutions, motion blur estimation is used in real-time video image applications.

The following are additional image restoration processes in various fields:

- Iris identification
- Medical imaging and Tomography
- Microscopy
- Observing satellites and space vehicles
- Radar imaging
- Valuable photograph recovery.

2. Major Challenges

The following are discussed as the main obstacles that image restoration and image de-blurring processes must overcome:

- Real-world images with non-uniform blurring types are more challenging to permit the necessary images for neural network training. Furthermore, while obtaining a training database with realistic motion blur is difficult, the process of gathering training images for a particular task, such as super resolution, is straightforward.
- The convolution method requires backgrounds and pixel-wise blurs kernels to contain moving objects in the input image. Despite this, object segmentation in images is so intricate that pixel-by-pixel blur kernel generation for non-uniform images is not feasible. Furthermore, occlusion in an image may result in a major loss of data that is necessary for processing.
- While the averaging model is expensive and limited in its scene range of application, it is designed for the purpose of image restoration. The trained network in these databases cannot be generalized, and the image database produced by the averaging system might not be very diverse. The current model-based optimisation methods do a poor job of addressing the extensive blur's long-range spatial dependency.
- Additionally, because of their limitations in the receptive field, CNNs are ineffective at aggregating this kind of dependency. (Gopatoti, & Gopathoti, 2017) [19].
- Additionally, a parametric method for image denoising has been developed; however, it is not suitable for non-static scenes and does not evaluate non-uniform blurs.
- Blurred images from outdoor scenes are very complex for de-blurring process, because of the complex three dimensional structures in blind motion de-blurring; additionally, optimisation process is complex along with uneven de-blurring and video de-blurring process is not performed in multi-image de-blurring approach.

3. Methodology

Here, we intend to build a brand-new KBNet, or kernel basis network, for use in picture restoration. The initial step in achieving flexible spatial information aggregation is to introduce the kernel basis attention (KBA) module. The next step is to introduce the multi-axis feature fusion (MFF) block, which can encode and fuse several features for imagery restoration. As a last topic, we will discuss the integration of the MFF block into the U-Net.

We develop an Adaptive Kernel Guidance Block (AKGB) and a foundational module to facilitate the efficient application of conditional information to diffusion models. The adaptive fusing of the dynamic kernels in each block of the diffusion model is achieved by combining the spatial guidance with extra scalar information. For a wide range of denoising tasks and uses (pictures, movies, etc.), we do extensive research in both virtual and physical settings. Over denoising, we evaluate many methods.

3.1 Kernel Basis Attention Module

Our proposed solution involves using the KBA module to encapsulate spatial information by adaptively fusing learnable kernel bases. This should solve these concerns. If we use a feature map as input, as seen in Figure 1,

$$X \in R^{HWC}$$

In order to identify similar spatial patterns, our KBA learns a collection of shared kernel bases W that are applicable to all pictures and locations.

These learnable kernels are built $W \in R^{N\times C\times 4\times K2}$ has N unique convolution kernels. The channel number is denoted by C, while the kernel size is denoted by K2. This group has a size of $\frac{C}{}$ in order to strike a balance between efficiency and performance.

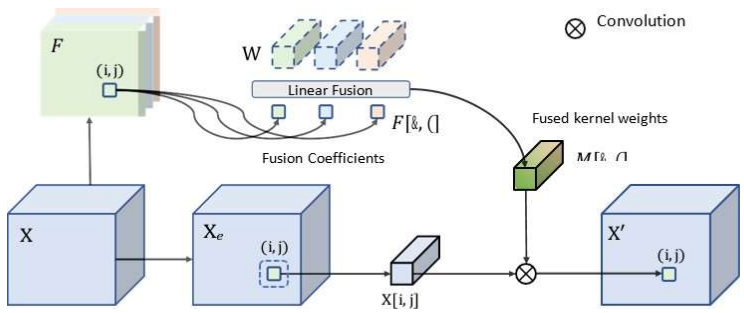

Fig. 1 Kernel basis attention (KBA) Module overview.

3.2 Multi-axis Feature Fusion Block

To handle channel and spatial information for encoding different attributes for picture restoration, we construct an MFF block using the KBA module. Figure 2 shows that the MFF block uses a layer normalization to stabilize the training and then aggregates spatial information. If you want your training to converge faster, you may use a residual shortcut. Three operators are used concurrently following the normalizing layer. To begin, characteristics that do not change regardless of location are captured using a 3×3 depthwise convolution.

3.3 Multi -axis Feature Fusion (MFF) Block

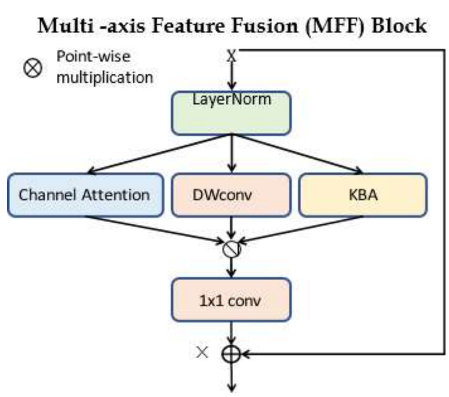

Fig. 2 An overview of the MFF Block, or Multi-axis Feature Fusion. The input features are processed in parallel by our KBA module, channel attention, and depthwise convolution. Point-wise multiplication is used to combine the outputs of three processes.

3.4 Intergration of MFF Block into U-Net

The U-shape architectures are commonly employed by us. After receiving a chaotic input picture, the U-shaped architecture processes it. $I \in R^{H\times W \times 3}$in order to produce a pristine image with the identical resolution. The feature map is created from the input picture by use of the first convolution layer,

$$F \in R^{H\times W \times C}$$

3.5 Intergration of Diffusion Model Block

To improve the integration of the conditional information into the block, we suggest a Conditional Integration Module (CIM). The CIM recommendations are first adjusted such that they match the resolution of the block's feature map. After scaling the guidance, it is sent through two convolution layers activated with a Simple Gate to form the feature map G. The channel number is changed in this way. Concurrently processing the auxiliary scalar data through a two-linear-layer branch with Swish activation in between results in the feature map S.

In order to generate dynamic kernels for the second convolution layer of the basic module, the feature maps G and S are then sent to the Adaptive Kernel Guidance Module (AKGM). Each spatial location may manage the feature map utilizing the fused various sources of conditional information, thanks to the AKGM's basic idea of adaptively fusing the kernel bases. Figure 2 (left) shows that in every AKGM, there are N learnable kernel bases, which are represented as $W_b \in R^{C\times C\times k\times k}$ where C is the channel count and k is the kernel size. These kernel bases can handle a wide variety of instances and scenarios thanks to their training. An intermediate Swish activation encoded two-linear-layer branch represents the scalar data (e.g., time). These feature 11 maps $G \in R^{H\times W \times N}$ and $S \in R^{1\times 1\times N}$ produce the multi-source fusion weights by merging them using point wise production $M \in R^{H\times W \times N}$. In this case, N is the quantity of kernel bases, while H and W are the feature map's height and width, respectively. Linearly fusing the kernel bases according to the multi-source fusion weights at the same place yields the fused kernel for a given point (i, j), denoted as F(i,j). It is formally stated as

$$F_{i,j} = \sum_{b=0}^{N-1} M_{i,j}[b] W_b \qquad (1)$$

4. Data analysis

4.1 Gaussian Denoising Results

Our KBNet uses half the computing cost to get state-of-the-art outcomes. Fig. 3 presents a few visual outcomes.

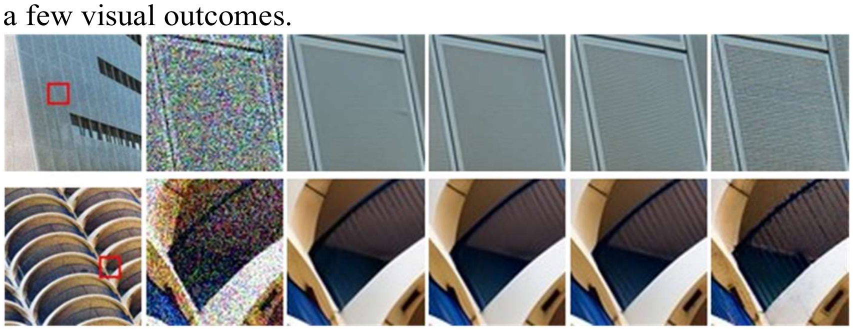

Fig. 3 Results of visualization using the Urban100 dataset's Gaussian denoising of color images. KBNet is able to retrieve finer textures.

4.2 Raw Image Denoising Results

The performance-efficiency comparisons of our technique are displayed in Figure 4. KBNet makes the optimal trade-offs.

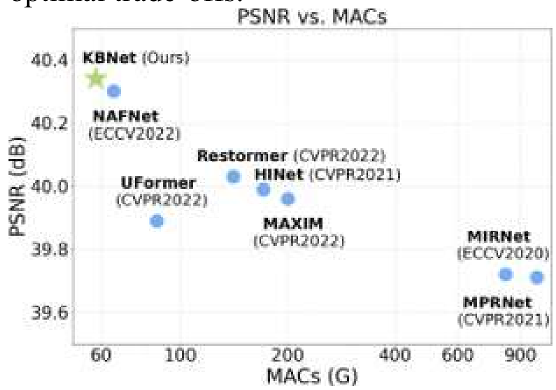

Fig. 4 PSNR vs MACs of several techniques for real-world image noise reduction using SIDD dataset.

4.3 Comparisons on Extreme Low-light Denoising

Our approach is evaluated for its performance on extreme low-light denoising by comparing it to the official implementations of transformer-based and convolution based backbones on the SID dataset. Since the SID dataset consists of high-resolution pictures, we are able to achieve full-resolution picture inference without grid artifacts using our inter-step patch dividing method. The numerical results demonstrate that our method outperforms the alternatives across all four parameters used to evaluate visual quality. As seen in Figure 5, the regression models provide more distorted results, but their visual quality is quite poor. The results of all of these methods are frequently quite vague. In contrast, our method offers superior perceptual qualities by producing images that are clear and detailed while also displaying vivid colors and intact structures.

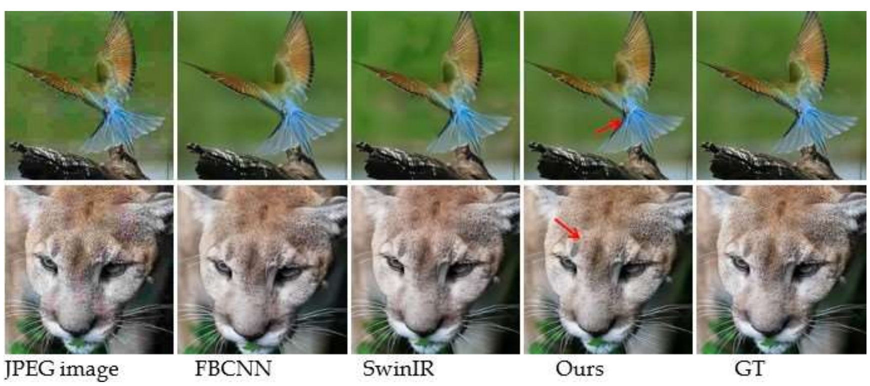

Fig. 5 Qualitative comparison on the JPEG restoration.

4.4 Comparisons on Image Deblurring

We also compare our model to popular deblurring methods and test it on the GoPro dataset. Since the software behind the diffusion-based approach has remained secret, we decided to build our methodology, DvSR, on an open-sourced project. Setting up a DvSR origin training environment that requires 32 seconds of TPU is challenging to reproduce. We train DvSR using our method's minimum training setting. The findings of the original study and the replicated study on perceptual quality are in agreement.

4.5 Comparisons on JPEG restoration

We compare our technique with other baseline models, such as diffusion-based method DDR and regression models (FBCNN and SwinIR) for the JPEG restoration job.

Table 1 JPEG restoration results on ImageNet

	Perceptual		Distortion			
Model	LPIPS↓	NIQE↓	FID↓	KID↓	PSNR↑	SSIM↑
SwinIR[31]	0.205	8.95	65.81	22.9	28.00	0.883
QGAC [16]	0.260	-	-	-	28.01	0.800
FBCNN [23]	0.211	8.70	68.29	24.13	27.81	0.878
DDRM [26]	0.260	8.34	74.45	24.87	27.68	0.780
Regression	0.217	9.68	74.38	27.47	27.91	0.807
Ours	0.139	6.92	38.74	6.30	27.75	0.808

4.6 The Effectiveness of Inter-step Patch-splitting Strategy

In Fig. 6, we provide a visual comparison between the conventional patch-splitting method and our proposed inter-step method. The conventional approach clearly produces noticeable artifacts at the edges of patches, and adjacent patches fail to deliver consistent content. Adding more padding to the overlapping patches does not fix the issue. In contrast, our inter-step patch-splitting method produces more aesthetically pleasing and uniform results.

Table 2 The extreme low-light denoising dataset's ablation investigations.

Model	LPIPS↓	MACs↓
w/ → w/o LayerNorm	0.227 0.240	71.7
Swish → ReLU	0.235	71.7
w/o Spatial guidance	0.240	70.9
Internal feature guidance	0.247	72.1
Degraded image guidance	0.253	71.7
Addition	0.236	71.5
Concatenation	0.241	112.7
AdaIN [21]	0.240	71.5
DvSR [50]	0.244	73.7
Ours	0.222	71.7

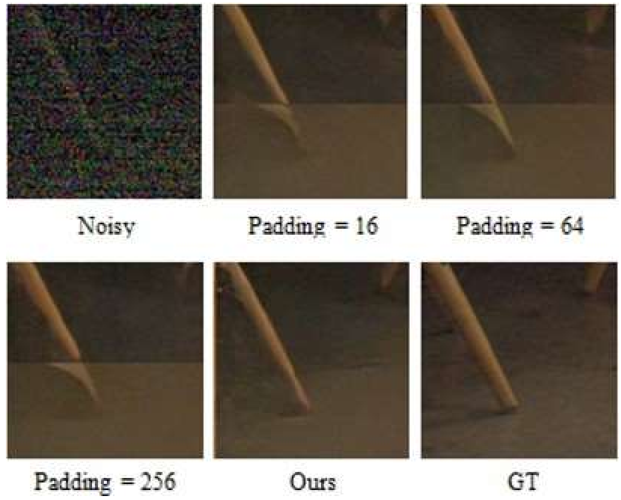

Fig. 6 The visual comparison on different patch-based splitting strategy.

4.7 Understanding the Denoising Performance

While finding the theoretical limit of compared image denoising algorithms is challenging, it is interesting to see how comparable approaches denoise images in challenging real-world scenarios without access to previous data like camera settings and training/- validation datasets. For each scenario in the FUJIFILM X100T camera dataset from our IOCI, we average three, five, and ten noisy shots to get three new mean pictures (Mean 3, Mean 5, and Mean 10). One way to look at these images is as a collection of continuous photography settings shot at different noise levels (high, medium, and low). On the FUJI dataset, Fig. 7 shows the average PSNR disparities between Mean 3 and six different implementations. It is worth noting that Fig. 18 shows that even the most advanced denoising algorithms perform about the same as Mean 3, which is calculated by averaging three consecutive noisy data, with only minor gains.

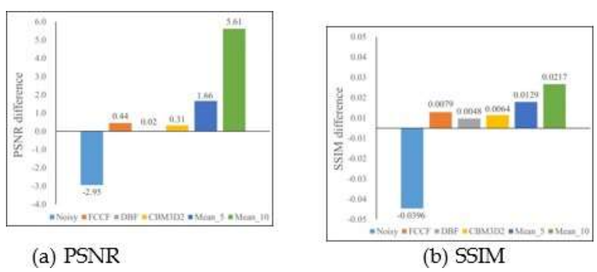

Fig. 7 PSNR and SSIM difference of six implementations compared with 'Mean3' on the FUJI dataset.

4.8 Pre-Training Cost

The remarkable ability of several DNN algorithms to utilize extra data for pattern recognition in noise and the creation of camera aware noise models makes them powerful. Training could be time-consuming despite the many benefits of DNN denoising frameworks. In order to investigate the pre-training cost, we employ DANet that has been trained using the PolyU dataset. To be more specific, 20% of the clean/noisy pairs from each camera in the PolyU dataset are used for testing, while 80% are used for training. The training dataset is expanded by randomly rotating and flipping. Through the use of the authors' code, we train the DANet model for a maximum of 60 epochs, with the GPU device completing each epoch in around 15 minutes. Figure 8 displays that DANet surpasses CBM3D2 on the test set after 30 training epochs.

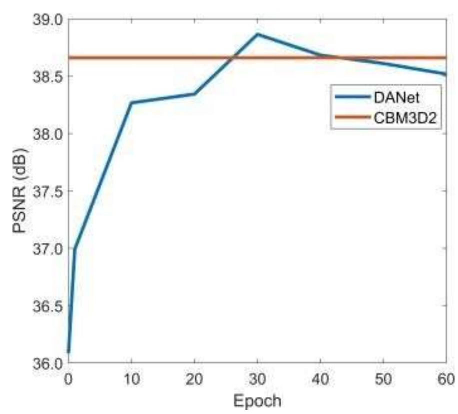

Fig. 8 PSNR and SSIM values of the DANet with respect to various training epochs on the PolyU test set.

5. Conclusion

We have assessed the performance of Kernel Basis Network (KBNet) in the areas of image restoration and denoising in this comparative research. Our tests show that KBNet performs better at recovering pictures distorted by various kinds of noise, such as Gaussian, salt-and-pepper, and Poisson noise, than a number of state-of-the- art techniques. Furthermore, KBNet demonstrates resilience in maintaining intricate picture features while successfully eliminating noise abnormalities. These findings demonstrate KBNet's potential as an effective tool for improving picture quality in a range of applications, including photography, surveillance, and medical imaging. Sub- sequent investigations might focus on enhancing the KBNet design and investigating its practicality in real-life situations. All things considered, our research highlights how important KBNet is to the advancement of picture restoration and denoising.

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