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A Review of Emerging Deep Learning Methods For Image Restoration.

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Abstract—Convolutional neural networks and other deep learning approaches have drawn a lot of attention in practically all fields of image processing, particularly picture categorization. Image restoration, however, is a fundamental and challenging problem that is important to image processing, comprehension, and representation. Image denoising, super-resolution, dehazing, and deblurring, are frequently covered. Numerous studies are being conducted in this field.Various machine learning and deep learning techniques are used for this. This paper examines various image restoration methods that focus on deblurring and super-resolution.

Index Terms—Machine learning, Deep learning, Generative adversarial network, Convolutional neural network

I. Introduction

Image restoration is recovering the original image from the degraded image. Degradation has various forms such as motion blur, noise and camera misfocus. Image noise is a random variation of brightness or colour information in the captured images. Image blur can be due to movement during image capture, atmospheric turbulence, and short and long exposure times. The fundamental goal of image restoration is to fix flaws brought on by blurry and noisy images. Image enhancement differs from image restoration in that it highlights aspects of the image that make it more aesthetically acceptable to the viewer rather than necessarily producing data that is realistic from a scientific perspective. It offers a wide range of potential applications like Computer vision applications, Object detection, Face recognition, Medical imaging, Remote sensing, and Planetary imaging. Image deblurring recovers a clear latent image from a blurred image that has been distorted by camera shakes or moving objects. In the domains of image processing and computer vision, it has drawn a lot of interest.

Image denoising involves taking out noise from the im-ages. The different intrinsic or extrinsic circumstances that contribute to the noise in the photographs can be challenging to deal with in image processing and computer vision. Image de-hazing is another image restoration technique. Image dehazing is a method that is becoming more and more popular for deal-ing with the deterioration of photos of the natural world caused by low visibility weather, dust, and other causes. The demand for low-complexity, high-performing dehazing solutions has increased as a result of developments in autonomous systems and platforms. And the next one is image super-resolution. Image Super-Resolution is increasing an image's resolution from low resolution (LR) to high resolution (HR).

The most common maximum likelihood or Bayesian ap-proaches in iterative algorithms are used in conventional meth-ods for image restoration. These methods also make use of sophisticated mathematics and probabilistic models to tackle inverse problems. Generally the formula of a degraded image Y is assumed to be the result of convolving a sharp image X with a blur kernel B which is added with noise N as follows,

$$Y = X * B + N$$

where $*$ denotes convolution operation. Sharp images can build by using degraded images. There are so many challenges faced by this process such as in the form of computational and performance quality. This study is mainly focusing on various image deblurring with enhancement techniques in deep learning.

II. LITERATURE REVIEW

A. Supervised, semi-supervised and unsupervised learning Strategies

1) Supervised learning: Supervised learning is a learning technique in which neural networks are trained using well-labelled data. It offers strong learning capabilities due to the minimization of cost functions across network layers. It pro-motes network convergence towards the intended distribution and the production of desired results.The design of the network architecture or the training strategy employed in CNN-based image restoration techniques focuses on non-blind settings with known or presumptive deterioration models. A single CNN cannot learn the conditional distribution of a high-quality image given a diversely degraded one. As a result, approaches for providing more prior knowledge to train a CNN have emerged. The restoration aim from a Bayesian perspective and how to reformulate the goal are more of J.W. Soh et al [1].'s attention. Similar to a divide-and-conquer tactic, the method breaks down the original posterior inference problem into smaller, more manageable sub-problems. The projected

framework improves the performance of numerous restoration problems. This technique offers leading-edge performance in particular for blind picture super-resolution, real-world noise reduction, Gaussian denoising, and JPEG compression mini-mization of compression artefacts.

In the study ”Super-resolving blurry face photos with iden-tity preservation” [2]., a deep learning approach based on identity preservation is proposed for super-resolving blurred facial photographs. To extract different levels of identity-related and semantic data, a recognition module is created and connected with a restoration module. The identity preservation data is used to inform the development of an assemble loss function, which regulates and directs the restoration and recog-nition process. Evaluations, both qualitative and quantitative, show that the suggested strategy to face repair is effective. The outcomes demonstrate that facial identity can serve as a reliable replacement for face image restoration.There are two modules in the framework. The goal of the restoration module is to provide high-resolution face photos and attributes relevant to facial identification. It has two upsample blocks and 32 residual blocks. Two convolutional layers and one ReLU are present in every residual block. A pixel-shuffle layer and a convolution layer make up the upsampling block. The remaining blocks are all covered by a skip connection. The top of the convolution layer is marked with the kernel size and channel number.

2) Unsupervised learning: UID-GAN [3] presents an un-supervised method for single-image deblurring without paired training images. The disentangled framework, which is shown here, separates the content and blur components of a blurred image and enhances deblurring performance. In order to ensure that the content structures of the restored results closely reflect the original images, a blurring branch and the cycle-consistency loss are introduced to manage the unpaired train-ing data.For extra artefact reduction, also include a perceptual loss to naturally deblur an image and a colour loss to lessen output colour aberrations. Useful datasets include CelebA, BMVC text, CFP, and COCO.

B. Adversarial learning

Generative models, or GANs, produce fresh data instances that mimic your training data. Zheng et al. [4] introduced an edge-GAN in which the network employs the coarse-to-fine end-to-end sharp picture restoration technique, which has a faster running speed because it does not rely on the blur kernel estimation. Additionally, it creates a hierarchical content loss model that considers the restored image's local and global quality details. Experiments have shown that the suggested network performs deblurring tasks better than other methods. The two datasets used are Kohler Benchmark and the GoPro Dataset. Recent research, however, demonstrates that GAN-based methods are superior at deblurring tasks. To improve the performance of GAN-based solutions on deblurring challenges, an edge-heuristic multi-scale generative adversarial network that employs the coarse-to-fine approach to restore clear images end-to-end is proposed.

Using super-resolution (SR), a low-resolution image is converted into a high-resolution image. To aid distinguish spacecraft and satellites from varied space debris, the Space Target Picture Resolution single image SR challenge was created. As a result of motion blur and great distances, images for space target SR are always of low quality. The low quality of images reduces the accuracy of manual classification for small space targets. An end-to-end Super Resolution and deblurring network [5] has been developed to address this issue are proposed that integrates SR and deblur function to improve the image quality of low-resolution space target photos with blind motion blur.In order to recover the texture information, a deblur module employing contrastive learning is constructed to extract degradation features and symmetrical downsampling and upsampling modules are added to the super-resolution network. In comparison to earlier SR approaches, SRDN (Super-Resolution and Motion Deblurring Network) performs better across the board in assessment criteria and can restore space target images with motion blur more successfully.

Recovery of a sharp image from a blurry image is known as image deblurring. Edge-based picture deblurring techniques ignore the image structures in favour of focusing on edge information for blind image deblurring. Here, the emphasis is on a picture deblurring technique that incorporates struc-tures and images with sharp edges. To give image structures guiding information, a structure-based deconvolution method utilising guided image filtering is created. The robustness of the salient edge selection in this case is increased by using the MAP framework to build a more expressive model with image structure and prominent edges [7]. For edge preservation and the reduction of details, a gradient is used. The technique performs better on benchmark datasets and in real-world situations, according to numerous experiments. Evaluations—both quantitative and qualitative—show that the technique is comparable to other strategies.

Recovery of consistently different spatial frequencies that the blur kernel has suppressed presents a hurdle in image deblurring. To solve this issue, existing image deblurring techniques rely on image priors such image gradients and edges. These priors can only be used to recover a subset of the frequency spectrum, such as frequencies at the high end..The S. Anwar et al. [6] proposed system, the focus is on the instance of a uniform blur, where a sharp image is convolved with a spatially homogenous blur kernel. So, given a blurry image Y, the goal of blind image deblurring is to identify the latent image x and the kernel k. Instead of using general gradient priors, the prior understanding of the distribution of frequency components is used to address the aforementioned issues. ETHZ dataset of shape classes, Yale-B face database, INRIA person dataset, and CMU PIE face dataset was used in the experimental validation. Randomly selected 10 to 15 sharp images from the other half of each dataset were used as deblurring test images, while the other half was used as training data. Eight complicated ground-truth blur kernels calculated by using test photographs as a source were used to create blurred images from those images.

TABLE I
COMPARISON OF THE STUDIED METHODS FOR IMAGE RESTORATION.

Method	Datasets	Pros	Cons
UID-GAN [3]	CelebA dataset, BMVC-text Dataset, CFP Dataset, COCO-Dataset.	Unsupervised method, Promising performance compared to other state-of-the-art approaches.	There are still artifacts in some images.
Edge Heuristic GAN [4]	GoPro Dataset,Kohler¨ Benchmark.	Not involve blur kernel estimation,faster running speed.	There are still artifacts in some images.
SRDN [5]	2-D subset of BUAA-SID Dataset.	Recover a superior image from an LR image.	Low performance in motion blur with LR.
Class-specific prior framework [6]	CMU PIE face dataset, Car dataset, Cat dataset, ETHZ dataset of shape classes, Yale-B face database, and INRIA person dataset	Outperforms prior deconvolution works	Confined by the concentrating single object comprising pictures and the assumption of spatially uniform blur
Salient edge combined with image structure in the MAP framework [7]	Levin's dataset, Kohler's¨ dataset,Lai's dataset	Time-saving because only straightforward filtering operations are required	Insensitive to photos that are fuzzy and have a lot of saturated pixels, and ineffectual to images that have a lot of noise.
SEN and RP-GAN [8]	Kohler dataset and GOPRO dataset	Better for large and complex motions	Need more optimization and simplification
MIRNet-V2 [9]	DPDD Dataset, DND dataset,SIDD, RealSR, LOL	Full resolution features and better-contextualized representations	Expensive in terms of size and speed.
GANs for median filtered [10]	BossBase V1.01, BOWS2, and UCID-V2.	Superior than current state-of-the-art techniques	Computational cost and time consuming is high.
VDIR [1]	BSD100, Urban100, DIV2K	Very effective blind denoiser	Need more optimization
Super-resolving blurry face images with identity preservation [2]	CelebA dataset	Obtain more identity-related features and preserve the identity information.	Need to improve the other special characteristics of face images.

A new architecture that aims to gain additional Contextual data from low-resolution images while preserving spatially accurate high-resolution images throughout the whole network is presented in this study by S. W. Zamir et al. [9].The architecture is centred on a multi-scale residual block that contains essential components such as concurrent multi-resolution convolution streams for extracting multi-scale attributes, information exchange throughout the multi-resolution streams, a non-local attention mechanism for gaining contextual information, and attention-based multi-scale feature aggregation. This method keeps the fine spatial details while also learning a bigger set of features that incorporate contextual data from various scales. Datasets show that the image processing technique MIRNet-v2 produces cutting-edge results for a number of tasks, includ-ing super-resolution,super-resolution, defocus deblurring, and image enhancement.

Jianyuan et al. [10] provide loss terms spanning three domains for MF image restoration and anti-forensics, and propose an adversarial learning system. The discrete wavelet transform domain's high-frequency coefficient variations are introduced as a word for restoring high-frequency components after a loss. Additionally, it is suggested that high-frequency sub-band variance loss in the discrete cosine transform domain will improve the closer statistical similarities between the generated and original images. In the spatial domain, a novel generator network is constructed in conjunction with the Huber loss and taught to improve feature reuse and information flow. As a discriminator that can separate the generated image from the original, a capsule network is used. The method achieves the best anti-forensic performance. is used. End-to-end learning-based techniques may not perform as well as optimization-based techniques. To achieve the goal, Junde Wu et al. [8] suggest integrating deep convolutional neural networks in to a traditional framework for deblurring to overcome their limitations. The Stacked Estimation Residual Net (SEN) and Recurrent Prior Generative and Adversarial Net (RP-GAN) are here proposed for estimating the motion flow map and learning the implicit picture, respectively, prior to optimization. The method recovers visual material more organ-ically and exhibits greater generalisation skills when compared to the most recent end-to-end learning-based approaches.

III. INFERENCE

The image restoration methods discussed above have their own merits and drawbacks. Evaluation indicators such as peak signal-to-noise ratio (PSNR) and structural similarity index matrix (SSIM) have been used to analyze the performance and accuracy of the restoration methods. Based on these assessments, a comparison of the above methods is given in TABLE 1. Edge heuristic GAN [4] is faster than other methods and gives better performance. The real challenge is solving the problem of image restoration in real-world images. This comparative study gives a better understanding for the same.

IV. CONCLUSION

Since image restoration is ill-posed, it is a difficult image-processing operation. The deterioration mechanisms and noise models are built using traditional methods, which rely on handcrafted models. In reality, noise models and degradation mechanisms are rarely homogeneous and overly simple. As a result, learning-based approaches are more useful and frequently perform much better than conventional ones. There has been a significant corpus of research on everything from super-resolution to deblurring, denoising, and dehazing, with a focus on deep learning networks. Also discussed was the design of the motion deblur and super-resolution system.

Unsupervised or semi-supervised learning has increasingly been integrated with supervised processes in picture restora-tion, Even though the vast majority of deep learning techniques are based on supervised learning since they can improve data representation. Further exploitation in this area might improve the effectiveness and efficiency of repair tasks.Graphs and self-organizing structures could be incorporated into the supervised learning methods in the deep networks to make the poorly posed inverse problems more realistic, more successful, and less reliant on a huge number of paired training samples.

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