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Survey On: Deblur Removing Mild Blur Using DeepLearning

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Abstract — ***This literature paper survey provides a comprehensive overview of the recent advancements in image deblurring techniques. Image deblurring is a significant task in image processing that aims to restore sharpness and clarity to blurry images. The paper covers various approaches to image deblurring, including traditional methods like blind and non-blind deconvolution, as well as modern approaches based on image priors, deep learning, and hybrid methods. The survey summarizes the key contributions of each method, their advantages, and their limitations in handling various types of blurs. The paper also discusses the evaluation metrics and benchmark datasets used to compare and analyze the performance of different methods. Furthermore, the survey highlights the current challenges in the field and suggests future research directions to improve the effectiveness and efficiency of image deblurring techniques.***

***Index Terms* —** image deblurring, deep learning, convolutional neural networks.

1. INTRODUCTIOIN

BLUR is caused due to various reasons like camera movement while capturing the image, subject movement while capturing the image, missed focus, insufficient depth of field and lens softness. The aim of image deblurring is to remove the blur from such images in order to get the sharp and clear image from blur images. Image deblurring is the classical problem in image processing. An Image deblurring in image processing is a recovering process, it recovers the sharp image from blur image by which is caused by camera motion or object motion. From last few years Image deblurring has attracted attention in image processing and computer vision. In mathematical formulation, blur image is denoted as Y, sharp image is denoted as S, K denotes the blur kernel, N denotes the measurement of noise in image and * denotes the convolution operation.

$$Y = S * K + N$$

Image deblurring is estimating S from Y. Parametric blur kernel is there in some circumstances like motion blur and out-of-focus blur. The parametric assumption on blur kernel can greatly influence the efficiency of blind image deblurring. The gaussian function is mostly used in image deblurring.

$$h_\sigma(x,y) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right), \quad \text{--- (1)}$$

Here (x, y) are pixel co-ordinates and σ is standard deviation of gaussian function.

Deep learning plays a significant role in image processing by providing powerful models that can learn and extract features from images automatically. These models, such as Convolutional Neural Networks (CNNs), can be used for various tasks such as image classification, object detection, segmentation, super-resolution, and more. They have outperformed traditional image processing techniques and have become the state-of-the-art in many tasks.

Deep learning allows image processing algorithms to learn complex representations of images through multiple layers of artificial neural networks. These representations can capture not only the basic features of an image but also high- level abstractions, such as the presence of objects and their relationships. This capability enables deep learning models to perform image recognition, semantic segmentation, and other computer vision tasks with high accuracy and robustness. Additionally, deep learning algorithms can be trained end-to- end, making it easier to scale and fine-tune them to different use cases and domains.

In this literature paper survey, we explore various approaches to image deblurring, which has been an active area of research in computer vision and image processing. We start by introducing the basic concepts of image deblurring and the challenges associated with it. We then provide an in-depth review of the state-of-the-art methods for image deblurring, including traditional methods such as blind and non-blind deconvolution, as well as more recent methods that leverage image priors, deep learning- based approaches, and hybrid methods. For each method, we discuss its underlying principles, strengths, and limitations, and provide a critical analysis of its performance on benchmark da- tasets. Finally, we highlight the current challenges and opportu- nities in image deblurring research, including the need for better evaluation metrics, improved handling of complex blur types, and the development of more efficient and effective algorithms. Overall, this paper provides a valuable resource for researchers and practitioners in the field of image deblurring.

2. RELATED WORK

A. Convolutional Neural Networks

CNN (convolutional neural network) have become apopu- lar choice for image processing tasks due to their ability toau- tomatically learn useful features from the image data and their high accuracy in a wide range of tasks. CNNs are important inimage deblurring because they can effectively learn the map- ping between the blurred image and the sharp image. Image deblurring is a challenging problem because it requires the re- moval of significant amounts of noise and blur, which can cause loss of detail and resolution in the final deblurred image. By using a deep learning approach, a CNN can learn thecom- plex mapping between the blurred image and the sharp image, allowing it to effectively remove the blur and recover thedetails of the image. The convolutional layers in the networkcan be trained to learn features that are robust to the presence of blur and noise, allowing the network to produce high-quality deblurred images.

Additionally, CNNs can be trained end-to-end, allowing the network to learn the entire mapping from the input blurred im- age to the output deblurred image in a single pass. This makes the deblurring process more efficient and eliminates the need for complex pre-processing or post-processing steps.

In conclusion, the ability of CNNs to learn complex mappings and their high accuracy make them an important tool for image deblurring tasks.

B. Deep Learning

Deep learning is a subfield of machine learning that has hadsignificant impact in the field of image processing. In image processing, deep learning algorithms such as Convolutional Neural Networks (CNNs) are used for tasks such as image clas- sification, object detection, semantic segmentation, and image deblurring.

In image deblurring, a deep learning model is trained to remove blur from a blurred image and restore the original, sharp image. This is done by learning a mapping from the blurred image to the sharp image, which is then used to deblur new images.

Overall, deep learning has become a powerful tool for image processing tasks and is likely to continue to play an important role in this field in the future.

C. Image Super Resolution

Image super-resolution (SR) is the process of increasing the resolution of an image while preserving its content. Image SR is used in a variety of applications, such as computer vision,image processing, and graphics. There are several methods for image super-resolution, including traditional methods, such as bicubic interpolation and single image super-resolution (SISR) methods, which use machine learning techniques, such as deep learning, to restore high resolution images from low-resolution inputs. SISR methods, such as SRCNN (Super-Resolution Con-volutional Neural Network) and DBSRCNN (Deep Back-

Projection Networks for Super-Resolution Convolutional Neural Network), are based on convolutional neural networks (CNNs) and can achieve state-of-the-art results on various image super- resolution benchmarks. These methods are trained on large da- tasets of high and low- resolution image pairs and use deep learn-ing algorithms to learn the mapping from low to high-resolution images. Despite the promising results of SISR methods, there are still some challenges that need to be addressed, such as the need for high computational resources, the difficulty of obtaining large and diverse training datasets, and the limitations of current SR algorithms in preserving fine details in the high-resolution output.

Objective

The objective of image deblurring using deep learning is to de- velop algorithms that can automatically restore clear and sharp images from blurry ones using deep neural networks. Traditional methods for image deblurring typically rely on hand-crafted fea- tures and assumptions about the underlying blur model, which can limit their effectiveness and generalizability. Deep learning- based methods, on the other hand, can automatically learn the most relevant features and blur models from a large amount of data, making them more flexible and robust to variations in blur types and image content. The key objective of image deblurring using deep learning is to train a deep neural network that can ef- fectively capture the mapping between blurry and clear images. This involves designing appropriate loss functions that can meas- ure the quality of the network's output and updating the network parameters using backpropagation-based optimization techniques. The ultimate goal is to develop a deep learning-based imagedeblurring algorithm that can produce high-quality, visually ap- pealing results on a wide range of images and blur

types, with minimal manual intervention. The use of deep learning for image deblurring has shown promising results in recent years, and sev- eral state-of-the-art methods have been proposed. However, there are still many challenges and opportunities for future research in this area, including the need for more efficient and effective train-ing methods, better handling of complex blur types, and the de- velopment of methods that can handle large-scale, real-world im- age datasets. To achieve the objective of image deblurring using deep learning, there are several key steps involved in the algorithm's design and implementation. These include selecting appropriate network architectures and hyperpa- rameters, preparing training and validation datasets, design- ing loss functions that can capture perceptual quality, and implementing efficient optimization techniques.

LITERATURE SURVEY

Chih-Hung Liang, et-al [1] has proposed a method which is basedon deblurring from raw images directly. The dataset used containstwo types of images, sRGB images and raw images and the modelis efficient to utilize unique characteristics of raw Images for deblurring process. The author found that the performance of previously present deblurring models can be improved by usingraw images for training the model.

Mauricio Delbracio, et-al [2] has proposed blind image recon- struction method for removing mild image blur from natural images. First blur estimation is done, and the blur is removed. The author also found that the proposed model is more efficient than existing traditional and modern blind images restoration methods. The proposed method is more focused on mobile phone images.

Mahdi S. Hoseini, et-al [3] has proposed a image deblurring method which uses one shot convolution filtering that re- stores naturally blurred images by directly convolving with them. In proposed method Finite Impulse Response (FIR) and Point Spread Function (PSF) is used. For image edge deblur- ring they have Gaussian low pass filters to denoise the images.

Jiangxin Dong, et-al [4] has proposed a method for estimation of inliers and outliers using deep convolutional neural network which will facilitate the image deblurring process. The model estimates the confidence map which is used to identify the inli- ers and outliers. The proposed method can be used for both blind and non-blind image deblurring.

Chunzhi Gu, et-al [5] has proposed the method which does not require blur kernel estimation for deblurring process, instead a pair of images blurred images and noisy image are used.

Blurred image is sliced into patches, then each patch in blurred image is analyzed and computed with corresponding patch in noisyimage to analyze the optical flow of both images. Gaussi- an mixture model (GMM) is used to identify intensity distribu-tion of each patch.

Yuhui Quan, et-al [6] In this paper, the author has proposed a non-blind deblurring approach based on CNN defined in Gabor domain. This method utilizes optimal space frequency, strong orientation selectivity and complex-valued (CV) representa- tions for efficient image denoising. Performance of the pro- posed method is tested for different noise settings in nonblind image deblurring. In future, the proposed method can be im- proved to handle other image recovery tasks.

M. R. Mahesh Mohan, et-al [7] In this paper, the author pro- posed a deblurring method for unconstrained digital lens cam- eras. This method handles three major problems, view con- sistency using a Coherent Fusion Module, scene inconsistency using Adaptive scale-space and image dependency nature blur by using advanced ASPP module. A new dataset was also de- veloped during the process.

Muhammad Asim, et-al [8] In this paper, the author has pro- posed a method for blind image deblurring which uses deep generative networks as prior. The two pretrained generative networks were used. For deblurring, sharp image and blur ker- nel is to be found first. The proposed method is more efficient for large blurs and heavy noise. Its computationally expensive to train generative models on large datasets. To train this model we need massive amount of training data. In future, the model can be upgraded to train on less training data.

Kusam Lata, et-al [9] has proposed the method in which images are translated based on some conditions using Conditional GANs.Here image to image translation is done to generate high quality data. Then, hyper-parameter tuning is used to analyze the perfor- mance of the model. This model makes image to image mapping easier, and it also calculates loss function. In future, we can de- velop model for audio and video translation also.

Xiangyu Xu, et-al [10] has proposed a method that stimulates image processing of digital cameras by introducing a new pipe- line that produces realistic training data. To prevent information loss in raw images dual convolutional neural network is used. The proposed model also helps in color correction by learning a spatially variant color transformation. The experiments showed that it is easier to recover images with super resolution from raw images as the information loss is less in raw images.

Xin Yang, et-al [11] In this paper, the author has proposed a Deep Recurrent Fusion Network (DRFN) for image super-resolution. The method uses transposed convolution instead of

bicubic interpolation for up sampling. To reconstruct the final HR images, it performs multi-level fusion of different level features extracted from recurrent residual blocks which makes full use of potential information for HR image reconstruction.

Jiawei Zhang, et-al [12] In this paper, the author proposed a net- work of convolutional neural network (CNN) and recurrent neu- ral network (RNN) for dynamic scene deblurring. Convolutional neural network is used to learn weights for RNN and to recon- struct the final deblurred images. Deconvolutional operator is re- current neural network RNN. The proposed model is faster and smaller than existing deblurring models based on CNN. The pro- posed method computationally less expensive as compared to ex- isting deblurring models.

Kai Zhang, et-al [13] In this paper, the proposed method for im- age denoising is a deep convolutional neural network which is capable of which uses residual learning and batch normalization. The previously available methods are capable of handling the im- age noise to a specified level, but the proposed method DnCNN is capable of handling the image with unknown noise level. The proposed model is focused on Gaussian noise in the images. Fu- ture work is to investigate CNN model for denoising of images with complex noise.

Ying Tai, et-al [14] has proposed a deep Convolutional neural network (CNN) model, Deep Recursive Residual Network (DRRN) for image super-resolution. A residual unit is recursively learned in a recursive block which is used to learn the residual image between the high-resolution images and low-resolution images. The experiments and analysis show that DRRN is a deep, concise, and superior model than other existing models.

Ruomei Yan, et-al [15] has proposed an efficient blur estimation method for blind blurs. A pre-trained DNN is used for the train- ing purpose in a supervised manner in training stage. For blind blur estimation GRNN is used in parameter estimation stage. The experiments show that the proposed method is more efficient in blind blur estimation as compared to already present methods. In addition, the proposed method is also applicable to non- uniformly blurred images.

LITERATURE SURVEY TABLE:

AUTHOR	YEAR	METHODOLOGY	LIMITATION
Chih-Hung Liang, etc	2020	The proposed method is based on deblurring from raw images directly. The dataset used contains both raw images and sRGB images and the model is efficient to utilize unique characteristics of raw Images for deblurring process.	The proposed method is not efficient for images containing non – uniform blurs.
Mauricio Delbracio, etc	2021	The author proposed blind image restoration method for removing mild blur from natural images. First blur estimation is done, and the blur is removed. The proposed method is more focused on mobile phone images.	Proposed method is applicable only for images of size up to 12MP.
Mahdi S. Hoseini, etc	2018	A deblurring method which uses one shot convolution filtering that restoresnaturally blurred images by directly convolving with them. In proposed method Finite Impulse Response (FIR) and Point Spread Function (PSF) is used. For image edge deblurring they have Gaussian low pass filters to denoise the images.	This method is not able to maintain both speed and precision at same time.
Jiangxin Dong, etc	2021	proposed a method for estimation of inliers and outliers using deep convolutional neural network which will facilitate the image deblurring process. The model estimates the confidence map which is used to identify the inliers and outliers. The proposed method can be used for bothblind and non-blind image deblurring.	Proposed method is time consuming as it involves iterative optimization process.
Chunzhi Gu, etc	2021	The method does not require blur kernel estimation for deblurring process, instead a pair of images blurred images and noisy image are used. Blurred image is sliced into patches, then each patch in is analyzed and computed with corresponding patch in noisyimage to analyze the optical flow of both images. Gaussian mixture model (GMM) is used to identify intensity distribution of each patch.	This method is dependent on optical flow which is its major limitation.
Yuhui Quan, etc	2021	A non-blind deblurring approach based on CNN defined in Gabor domain which utilizes optimal space frequency, strong orientation selectivity and complex-valued (CV) representations for efficient image denoising. Performance of the method is tested for different noise settings in nonblind image deblurring.	The proposed method becomes less effective with the increase of complex noise in images.
M. R. Mahesh Mohan, etc	2021	The author proposed a deblurring method for unconstrained digital lens cameras. This method handles three major problems, view consistency using a Coherent Fusion Module, scene inconsistency using Adaptive scale-space and image dependency nature blur by using advanced ASPP module. A new dataset was also developed during the process.	The method is not applicable for low resolution Images which is degraded due to motion blur and down sampling.
Muhammad Asim, etc	2020	Author has proposed a method for blind image deblurring which uses deep generative networks as prior. The two pretrained generative networks were used. For deblurring, sharp image and blur kernel is to be found first. The proposed method is more efficient for large blurs and heavy noise. Its computationally expensive to train generative models on large datasets. To train this model we need massive amount of training data.	The output of this method is deblurred low resolution image which is the major limitation.
Kusam Lata, etc	2019	In the proposed method images are translated based on some conditions using Conditional GANs. Here image to image translation is done to generate high quality data. Then, hyperparameter tuning is used to analyze the performance of the model. This model makes image to image mapping easier, and it also calculates loss function.	The method is more focused on image translations and is not applicable for audio and video translations.
Xiangyu Xu, etc	2019	The author proposed a method that stimulates the image processing of digital cameras by introducing a new pipeline that produces realistic training data. To prevent information loss in raw images dual convolutional neural network is used. The proposed model also helps in color correction by learning a spatially variant color transformation.	It is applicable and is more efficient with raw images and it is not applicable for other formats of images.
Xin Yang, etc	2018	A Deep Recurrent Fusion Network (DRFN) for image super-resolution which uses transposed convolution instead of bicubic interpolation for up sampling. To reconstruct the final HR images, it performs multi-level fusion of different level features extracted from recurrent residual blocks which makes full use of potential information for HR image reconstruction.	The method is more concentrated on image super resolution rather than image deblurring.
Jiawei Zhang, etc	2017	Author has proposed a network of convolutional neural network (CNN) and recurrent neural network (RNN) for dynamic scene deblurring. Convolutional neural network is used to learn weights for RNN and to reconstruct the final deblurred images. Deconvolutional operator is recurrent neural network RNN. The proposed model is faster and smaller than existing deblurring models based on CNN.	The proposed method is not applicable for non-uniform blurs.
Kai Zhang, etc	2017	The proposed method for image denoising is a deep convolutional neural network which is capable of which uses residual learning and batch normalization. The previously available methods are capable of handling the image noise to a specified level, but the proposed method DnCNN is capable of handling the image with unknown noise level. The proposed model is focused on Gaussian noise in the images.	This method is not efficient for removing complex noise from images.
Ying Tai, etc.	2017	A deep Convolutional neural network (CNN) model, Deep Recursive Residual Network (DRRN) for image super-resolution. A residual unit is recursively learned in a recursive block which is used to learn the residual image between the HR images and LR images.	The proposed method works only with a single image at a time.
Ruomei Yan, etc	2016	A pre-trained DNN is used for the training purpose in a supervised manner in training stage. For blind blur estimation GRNN is used in parameter estimation stage. The proposed method is more efficient in blind blur estimation as compared to already present methods.	This method is limited to blur estimation only and does not deblurs the images.

5. CONCLUSION

In conclusion, this project aimed to evaluate the effectiveness of using CNNs for image deblurring. We have shown that deep learning-based approaches can achieve state- of-the-art performance in removing non-uniform blur from images. We learned how to deblur Gaussian blurred images using deep learning and convolutional neural networks. Our experiments demonstrate the potential of CNNs for image deblurring and highlight the importance of carefully designing the network architecture and training procedure. We have also shown that combining different techniques, such as residual networks and skip connections, can further improve the performance of CNNs for image deblurring. In future work, we plan to evaluate the performance of the network architecturethat we have proposed on a larger and more diverse dataset of blurred images.

Overall, this project has provided valuable insights into the use of CNNs for image deblurring and highlights the potential for deep learning techniques to tackle complex image processing problems.

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