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Motion Blur Detection and Removal in Images

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Abstract:- Image blur detection and removal have been one of the major topics of research in image processing in the recent years. These blur detection and removal algorithms have many real world applications including image restoration and image enhancement. Image blur can include motion blur and out-of-focus blur or blurring due to lens imperfections. This paper covers an overview of recent methods and advancements made in the fields of motion blur detection as well as motion blur removal. This paper also proposes an approach for motion blur detection and removal involving Convolutional Neural Network(CNN) and Generative Adversarial Network(GAN).

***Keywords*:-** *Motion Blur, Out-of-Focus Blur Detection, Blur Removal, Image Restoration.*

I. INTRODUCTION

One of the frequently encountered problems in photography as well as capturing a video is the introduction of blur either due to object movement or camera motion associated with the speed of the camera (shutter speed) when pictures are taken. Blur is the smoothing of the image pixels essentially resulting in a relatively obscure image. To counter this problem the initial step is blur detection where the part of the image where the blur has occurred is identified. After this the blur is classified into general blur and motion blur. The last step is the image restoration step where blur is removed. This paper discusses some approaches used to detect and remove motion blur. This paper also proposes a deep learning based approach on detection of blur, targeting mainly motion blur and not a plain defocused image by using a culmination of different methodologies and once detected, work on remediating it using Generative Adversarial Network in order to restore it or rather regenerate the original image.

II. LITERATURE SURVEY

Renting Liu, Zhaorong Li & Jiaya Jia [1] proposed a partial-blur image detection along with a framework that analyses and classifies types of blurs without the need of deblurring. They used several blur features derived by colors from an image along with it's spectrum & gradient information & used these feature parameters to robustly train & classify blurred images. The blur is classified as either motion blurred regions caused due to motion of subject or out-of-focus blur which is generally caused by lenses being out-of-focus from subject in an image.

Beomseok Kim, Hyeongseok Son, Seong-Jin Park, Sunghyun Cho, and Seungyong Lee [2] put forward a novel approach for detecting two types of blurs - motion blur and out-of-focus blur. They proposed a method that used a deep encoder-decoder network with long residual skip-connections along with multi-scale reconstruction loss functions to make use of low-level structural features as well as high-level contextual features. This research outperforms other state-of-the-art methods. However this research was performed on a limited size of dataset without considering complex cases of blurs in an image.

Karl S. Ni, Zachary Z. Sun & Nadya T. Bliss [3] proposed an algorithm to detect global motion blur from a video source. The working of the algorithm is two fold, firstly the algorithm creates a blur metric from any single frame or image and secondly, it adds temporal information by making use of correlated information from adjacent frames from a video feed. The advantage of this algorithm is that it makes use of adjacent reference frames from videos compared to just blur detection from still images. Additionally it is easy to understand and outputs high performance for blur detection.

Bing Li, Zhen Huan Zhan [4] discussed recovering a degraded image using linear and inverse filter methods. Motion blurred distance and motion blurred direction are the parameters used in the recovery process of blurred images. The authors used mean square error for comparing the quality of image between restored image and blurred image.

Taeg Sang Cho [5] discussed a kernel based spatially invariant blur detection method that uses blurred-edge profiles. The research proposed both a hardware and a software solution for blur detection and it's removal. The software based solutions involve blur kernel estimation through blurred line profiles and using phase information while the hardware solution involves using a camera that improves local motion estimation using computations.

Dong Gong, Jie Yang [6] proposed a pixel wise linear motion blur representation for heterogeneous motion blur. The method the authors proposed estimates a dense motion flow map using a fully-convolutional deep neural network. The dataset they used consists of both real world and synthetic images. The research shows promising results for real world images containing heterogeneous motion blur.

Shuang Zhang, Ada Zhen [7] put forward an approach wherein a pair of images as input are subject to denoising and deblurring encoders after which they are merged and passed through a deblurring decoder. The two encoders are used to extract the complimentary information from the pair of images. The merger is done to combine the information in parallel. However a prerequisite for their model are pairs of blurry images which is a drawback.

Jian Sun, Wenfei Cao, Zongben Xu & Jean Ponce [8] put forward a novel deblurring approach based on convolutional neural networks for images containing non-uniform motion blur. This deep learning approach is used for predicting probabilistic distribution of the motion blur at the patch level. A Markov random field is used to enforce motion smoothness after which the motion blur is removed using a non-uniform deblurring model.

Jian-Feng Cai, Hui Ji, Chaoqiang Liu and Zuowei Shen [9] discussed a new approach to remove motion blur that is based on high sparsity of the motion blur kernel in the curvlet system and that of the image in the framelet system. The method requires no prior information on the kernel which makes it different from existing approaches. The algorithm was tested extensively on synthesized as well as real world images and shows promising results compared to existing approaches.

III. PROPOSED METHODOLOGY

A. Detection

In this section, we propose an end-to-end deep neural network for detecting motion blur and localizing it. The problem of motion blur can be assumed as a problem of semantic segmentation with the regions containing motion blur to be segmented. We propose the use of a Mask region-based convolutional neural network for this task. A Mask R-CNN is a convolutional neural network aimed to solve the instance segmentation problem. There are two stages in Mask R-CNN. First, the region proposal network generates proposals for the regions where an object might be present based on the input image. Second, it classifies the object, refines the bounding box, and generates a pixel level mask of the object based on the first stage proposal. [See fig. 1]

➢ *Homogenous regions:*

Some flat regions having the same colour are sometimes misclassified as blur in order to remediate this, we separately process the image as separate blocks of sizes 8x8 or 16x16 and then plot the standard deviation of the spectral intensities of the pixels. If the standard deviation is very low then we can understand that the region is essentially black and that there is no motion blur present the Intersection over Union is then taken for the combining the outputs of the standard deviation mask and the mask rcnn output.Essentially this makes our model more robust to any kind of image and improves the performance of the motion blur detection .

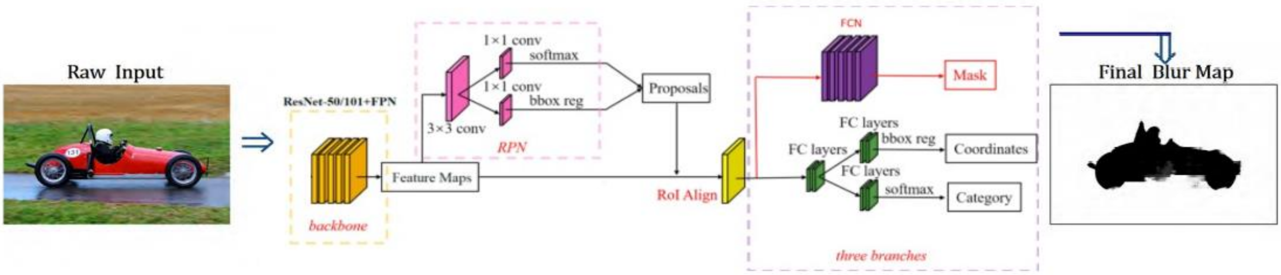

Fig 1:- Architecture diagram of proposed methodology for blur detection [10], [11]

B. Removal

In this section, we propose an end-to-end deep neural network for removing motion blur. This problem of removing motion blur can be assumed as a problem of deconvolving the PSF that leads to the blur. We propose the use of a Generative Adversarial Network for this task. GANs are an approach to generative modeling using deep neural networks. GANs will be used for training a generative model that will generate deblurred images.

➢ *Algorithm*

1. Train a custom Mask R-CNN[12] for semantic segmentation between non-blurry and blurry portions of the image.
2. Based on the pre-decided threshold, decide if the image is blurry or not. If blurry send to blur removal.
3. For blur removal train a GAN[13] with sharp and respective motion blurred images.
4. The image generated by the GAN generator is sent to the discriminator to calculate loss.
5. Based on the loss function generator and discriminator loss is calculated and back propagation is performed.

IV. CONCLUSION

This paper starts with the introduction of motion blur and its applications. Several motion blur detection and removal techniques were introduced. We also discussed approaches involving a single image as an input as well as a pair of images. We also discussed how encoders and decoders are effectively used to detect and remove motion blur. Lastly we proposed an approach involving a mask region-based convolutional neural network for detection and a Generative Adversarial Network based method for removal.

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REFERENCES

[1] Renting Liu, Zhaorong Li & Jiaya Jia, “Image partial blur detection and classification” in CVPR 2008.
[2] Beomseok Kim, Hyeongseok Son, Seong-Jin Park, Sunghyun Cho, and Seungyong Lee, “Defocus and Motion Blur Detection with Deep Contextual Features” in Computer Graphics Forum 37 (7) (2018)
[3] Karl S. Ni, Zachary Z. Sun & Nadya T. Bliss, “Real-time global motion blur detection” in 9th IEEE International Conference on Image Processing, 2012
[4] Bing Li, ZhenHuan Zhan, “Research on Motion Blurred Image Restoration,” in *5th International Congress on Image and Signal Processing*, 2012.
[5] Taeg Sang Cho, “Motion Blur Removal from Photographs ”, in . *M.I.T Ph.D dissertation (2010)*
[6] Dong Gong, Jie Yang, “From Motion Blur to Motion Flow:a Deep Learning Solution for Removing Heterogeneous Motion Blur”, CVPR, 2017
[7] Shuang Zhang, Ada Zhen, “Deep Motion Blur Removal Using Noisy/Blurry Image Pairs”, Cornell University, 2019
[8] Jian Sun, Wenfei Cao, Zongben Xu, Jean Ponce, “Learning a Convolutional Neural Network for Non-uniform Motion Blur Removal” , CVPR, 2015
[9] Jian-Feng Cai, Hui Ji, Chaoqiang Liu and Zuowei Shen, “Blind motion deblurring from a single image using sparse approximation”, CVPR, 2009
[10] Xuewei Wang, Shulin Zhang, Xiao Liang, Hongjun Zhou, Jinjin Zheng, Mingzhai Sun, “Accurate and Fast Blur Detection Using Pyramid M-Shaped Deep Neural Network”, IEEE, 2019
[11] Wenjun Yu, Sumi, Fei Chen, Jaeho Choi, “Pedestrian Detection Based on Improved Mask R-CNN Algorithm” , Springer, 2020
[12] Ross Girshick, Jeff Donahue, Trevor Darrell, Jitendra Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation” in CVPR 2013
[13] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, “Generative Adversarial Networks” in “Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2”, 2014
[14] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, “Generative Adversarial Networks” in “Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2”, 2014
[15] Yandong Guo, Lei Zhang, Yuxiao Hu, Xiaodong He, Jianfeng Gao, “MS-Celeb-1M: A Dataset and Benchmark for Large-Scale Face Recognition”, 2016
[16] Gary B. Huang, Manu Ramesh, Tamara Berg, and Erik Learned-Miller. Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments.