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A novel generative model for disentanglingand deblurring of fast moving objects

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Abstract

Image blur is general artifacts in digital image processing and it is hard to avoid. Image enhancement or deblurring is necessary to reduce blur amount from the image. Image deblurring is a process used to reduce the blur quantity in a blurred image and make the degraded image into sharpened and clear image. When deblurring images, cause of blurring is very important to increase the effect of the deblurring to get good result. While working with real- time images, we may not have the knowledge of the reason of blurring.There are various sources why image gets blurred like motion blur, camera shake, out of focus blur, etc. This project carried out performance comparison of different techniques to diminish the effects of above mentioned causes of blurring. The analysis and comparison was conceded out based on types of blur, Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE) and Execution time.

INTRODUCTION

2.1 CAUSES OF BLUR:

The Images are blurred due to many reasons such as imperfections in capturing pictures, low intensityduring camera exposure, atmospheric problems etc. Yet imaging, just as any other observation process, is never perfect: uncertainty creeps into the measurements, occurring as noise, and other degradations in the recorded images. The image is a projection of the real world onto the lower dimensional imaging medium, a procedure that intrinsically discards information. Sometimes the information lost may contain things we are interested in: it can be beneficial to try to recover these hidden details. The current implementation of the Radon MAP algorithm requires quite a bit of memory. To solve for a 1 mega pixel image, it requires about 3-4GB of RAM memory .noise removal, often called motion deblurring or blind deconvolution, is challenging in two aspects. The first challenge is estimating blur kernels or point-spread functions (PSF) from blurred images. Because many noise–image pairs can explain the observed noisy image, blur kernel estimation is a difficult problem. Noise estimation can be especially difficult if the noise is spatially variant, for instance due to a dynamic scene or a camera rotation. The second challenge is removing the noise to recover a noise-free image. noise averages neighboring pixels and attenuates high frequencyinformation of the scene. Consequently, the problem of recovering a noise-free image is ill-posed, and it needs to be addressed by deblurring systems or algorithms.

- **OUT OF FOCUS**

It is blurring of an image due to incorrect focus. In optics, defocus image means an image is in out of focus. Detailed information in the image is blurred.

- **MOTION BLUR:**

It is blurring of an image due to movement of the object or imaging system. It is the apparent fast moving objects in an image. There are two types of motion blur Linear that in a single direction and circular can be in angle

- **GAUSSIAN BLUR**

It is the result of blurring an image by a Gaussian function. It is a widely used in many graphics tools to reduce the details of an image

3.1 Block Digram: Image Deblurring Technique

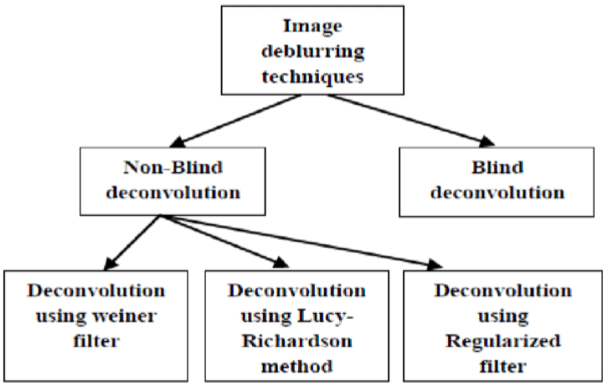

Fig. 1.1 Image blurring model of a camera.

BLIND DE CONVOLUTION

➢ Blind image deconvolution is the problem of recovering a sharp image (such as that captured by an ideal pinhole camera) from a blurred and noisy one, without exact knowledge of how the image was blurred.

➢ Blind deconvolution is more complex and more time consuming than the non-blind.

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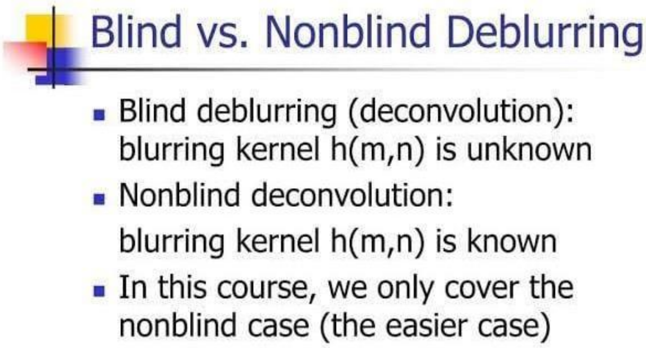
➢ while blind deconvolution is to restore the ideal image from the blurry image and the unknown blur kernel.

NON-BLIND DE CONVOLUTION

➢ Non-blind deconvolution is to recover theideal image from the blurry image with the known blur kernel.

➢ Non-blind deblurring is an integral component of blind approaches for removing image blur due to camera shake



. 4.1Blur Models :

The following section briefly describes some of the common blur types. The blurring functions are usually related to the following two classes:

- Space invariant These constitute the general form of blur PSFs that are independent of image pixel location. The blurring function produces a uniform blurring effect during convolution for each pixel location

. Space variant These constitute the blurring PSFs that create a different blurring effect depending on image pixel location. This results in the blurring effect being different for different pixels.

PSFs can be commonly distinguished in the following two groups based on their shape/form namely parametric and non-parametric:

- Parametric form These PSFs can be easily defined using a functional or parametric form. Usually an equation suffices to describe/generate the PSF. The PSF can be decomposed in a set of parameter(s) and can be reasonably approximated by these parameters.
- Arbitrarily shaped (non-parametric form) These PSFs usually have a complex shape and cannot be defined by an equation of their parameters. Decomposing the PSF in a set of parameters is not possible due to the complex shape of the PSF. Deblurring images corrupted

by such PSFs is a very challenging task.

5.1 Restoration Filters

The following section introduces the reader to some of the classical restoration filters that were used or studied in this research work

Inverse Filtering :The ideal approach to deblurring would be to estimate the inverse of the PSF that blurred the image and apply it to the blurred image and recover the original image. For a noiseless blurred image case, the direct inverse filtering can easily be applied in the spectral (frequency) domain [48], since the convolution process will be converted into multiplication. The inverse filtering process can be represented as F '□ G

Wiener Filtering :

As inverse filtering is very sensitive to additive noise which gets amplified during this process, a simple approach is to reduce single degradation at a time. Thus, the method allows us to develop a restoration algorithm for each type of degradation which can simply be combined afterwards. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework.

Iterative Blind Deconvolution Method:

The Iterative Blind Deconvolution (IBD) method makes use of the Fast Fourier Transform (FFT) and the deterministic constraints in the form of non-negativity and finite support constraints. Degraded image by g. Capital letters represent FFT versions of the corresponding signals. Subscript r denotes the iteration number of the algorithm. The iterative process can be summarised as follows:

1. First, a non-negative valued initial estimate f0 is input to the process.
2. This is Fourier transformed to give F‟r which is then inverted to form an inverse filter and used to form a new estimate of G, G‟r.
3. G‟r is then transformed by inverse Fourier Transform (iFFT) to give gr.
4. Then image non-negativity constraints are imposed to reveal a positive constrained estimate of gr.
5. gr is then Fourier transformed to give the spectrum of G‟r.
6. The spectrum G‟r is then inverted to form an inverse filter and multiplied by H‟r to estimate F‟r.
7. F‟r is then inverse Fourier transformed to give fr.

8. Image constraints are applied and an estimate of the image f‟r is achieved, this completes single iteration of the algorithm.

The iterative loop is repeated until two positive functions with the required convolution have been found. Unfortunately, the IBD algorithm suffers from two main problems:

- The inverse filter is difficult to define in regions where the inverted function possesses regions with low values.
- Spectral zeros at frequencies in either F‟r and G‟r provide no information about that spatial frequency being a part of the blurring process.

Implementation of this basic algorithm differs on the assumption on the true image and PSF, implementation of the assumptions and application in mind . The IBD method is popular because of its low complexity . Another advantage of this technique is its robustness to noise which results from the ill-posed nature of the blind image deconvolution problem. IBD algorithm also suffers from uncertain uniqueness, convergence, instability and sensitivity to initial image estimate.

Richardson-Lucy Algorithm

Richardson presented an iterative method of restoring degraded images based on Bayes‟ theorem of conditional probability.

Regularization Based Deblurring Algorithm

Looking into the convolution model of blurring presented the image estimate through inverse filtering is given by Eqnas follows

F'□ G □F□ V

Due to the ill-posed inverse problem, the restoration error will take very large values, particularly amplifying the high frequency noise .

6.1 Image Quality Measures (IQMs)

For BID, quality measures have been developed to evaluate the effectiveness of individual schemes or to evaluate different image processing algorithms. The performance of BID schemes in the past has been mainly subjected to error based performance measures that are already used by the existing signal processing community [48]. Most of these measures use an original and deblurred image pair to compute the error among them in order to construct a quantitative quality analysis. The original/uncorrupted image serves as a reference for high quality. In the past decade efforts were directed towards development of such quantitative

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image quality measures (IQMs) Error measures require both the original/reference and the observed/distorted image to be stationary with reference to each other; hence they do not allow any translational or rotational motion between the required images. Since the error measures require a reference imageto compute the quality against it, they are regarded as full-reference quality measures in this research work

7.1 Image restoration algorithms

usually based on some form of degradation model that establishes the relationship between an original and the blurred images of an imaging system. The blurred image isassumed to be the result of the convolution between the original image and the transfer function (degradation function) of the imaging system. The key to restoration is to estimate the degradation function. Any imperfection of the imaging system or environment can induce degradation to the captured image. If the image formation process can be modelled as a linear system, a recorded image can be represented as the output of the convolution of the spatial impulse response or Point Spread Function (PSF) of the linear blurring system with the original image (scene). Let m and n be the spatial image coordinates and fpresent the original image without any form of degradation, h be the PSF and the output of the system be given by g. Mathematically, for a stationary impulse response of the system across the image (i.e. a spatially invariant stationary PSF), the discrete form of the convolution according to is given by,

$g = h * f + v$

where * represents the 2-D convolution operator and v represents additive noise. Fig. shows the blurring model of a camera. The frequency domain model obtain edusing the Fourier Transform is,

$$G = HF + V$$

F= observe scene(image) h= impulse response g= captured image

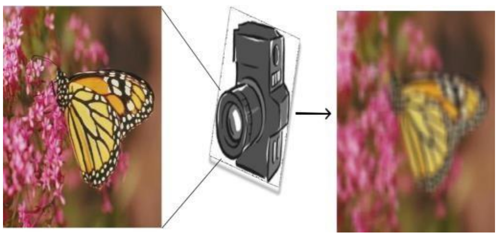

Fig. 71. Image blurring model of a camera.

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8.1 PERFORMANCE ANALYSIS OF DEBLURRINGMETHODS:

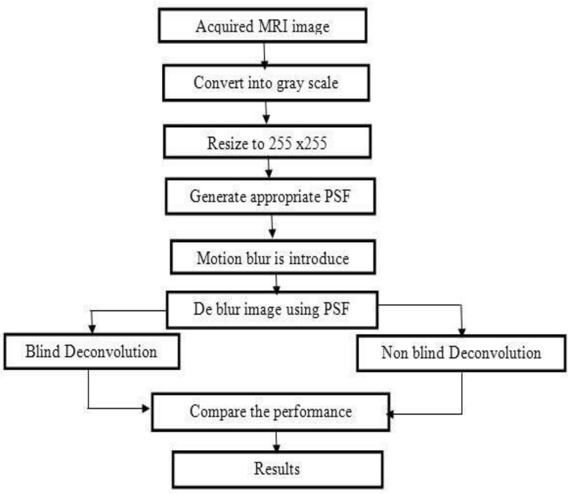
Methods name	Types of blur	Performance	PSNR ratio
Weiner filter	Gaussian blur	bad performance	17.05
Lucy-Richardson	Gaussian blur	Efficient	21.06
Regularized filter	Gausian blur	Efficient	20.10
Blind deconvolution	Gaussian and Motion	Efficient	26.78
Hyperspectral (PCA)	Hyperspectral image blur	Efficient	22.34
Neural network	Gaussian and out-of-focus	Very efficient	30.11
Motion density	Motion	Efficient	24.31

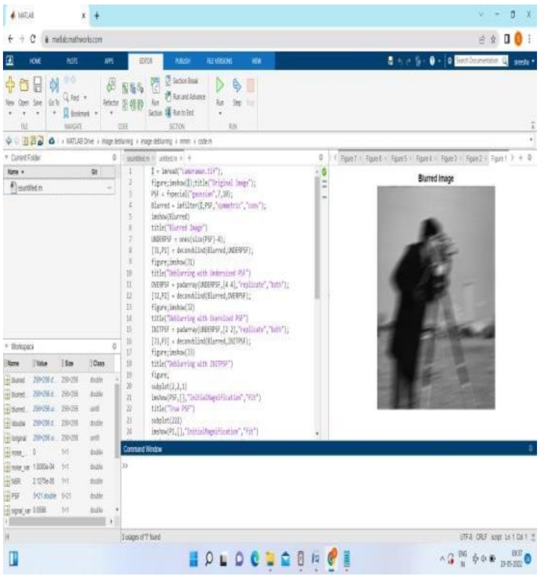
FLOW CHART PERFORMED:

- he blurring caused by certain reasons like out-of- focus, motion of an object or camera, Gaussian blur, etc.
- Recorded image has to be of a good quality. While using blurred image to get useful information for some applications, it is necessary to deblur the images.

Image deblurring is used to make images sharp and retrieve as much as detailed information from the image.

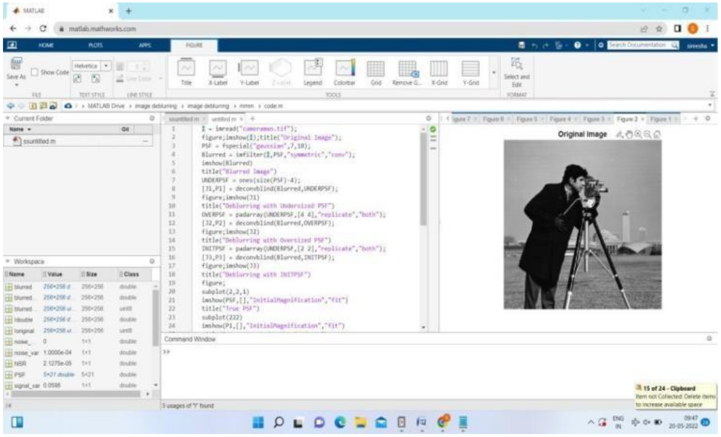
RESULTS:





Working:

Capture-time Solutions Short exposure time reduces blur, but increases noise and needlessly penalize static areas of the image. High speed cameras can capture fast motion, but require expensive sensing, bandwidth and storage. A high speed camera also fails to exploit the inter-frame coherence, while our technique takes advantage of a simplified model of motion. These cameras often require brilliant scene lighting. Edgerton and others [Edgerton 1951-1963] have shown visually stunning results for high speed objects using a modest exposure time but an extremely narrow-duration flash. Flash, however, isimpractical in outdoor or distant scenes. In addition, it captures an instant of the action and fails to indicate the general movement in the scene. Captured images are more or less blurry due to lot of interference in the environment and also in camera.



APPLICATIONS:

- CCTV and security camera footage
- Medical applications like scan,x-ray
- Iris recognition
- Face recognition
- Vehicle plate recongination

ADVANTAGES:

- IMAGE QUALITY IMPROVEMENT
- SHAPE RECOVERY OF OBJECT
- DEBLURRING OF OBJECT
- IMAGE RESTORATION

FUTURE SCOPE:

Blur is a common and unwanted artifact of image acquisition. There are many reasons why images become blurred such as movement, slow shutter speed or incorrectfocal distance. The idea is to make this approach is that it takes both the blurred and noisy image and as a result produces high quality reconstructed image. By using deblurring technique algorithm has been formulatedwhich will estimate a good initial kernel and reduce deconvolution artifacts. For our project, we researched multiple blind and non-blind deconvolution methods to gain an understanding of the current state of the art. Giventhe time limitations of the project, we were not able to probe much beyond this point, but we did learn of a few interesting and somewhat counter-intuitive properties of the convultion blur model. We also performed some experiments to acquire kernels directly from blurred images using cheap hardware. Finally, we implemented and compared several recent methods

7.1 Conclusion:

We proposed a novel generative model for disentangling and deblurring of fast moving objects. Training on a complex synthetic dataset with a carefully designed loss function incorporating prior knowledge of the problem scales well to real-world data. Experimental results show that the proposed model can handle fast moving objects with complex shapes and significant appearance changes within one video frame. DeFMO sets a new state of the art as it outerforms all previous methods on multiple datasets. Temporal super-resolution is among the possibleapplications.

References:

[1] Angel X. Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, Jianxiong Xiao, Li Yi, and Fisher Yu. ShapeNet: An Information-Rich 3D Model Repository. Technical Report arXiv:1512.03012 [cs.GR], Stanford University — Princeton University — Toyota Technological Institute at Chicago, 2015. 5

[2] M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, , and A. Vedaldi. Describing textures in the wild. In CVPR, 2014. 5

[3] Blender Online Community. Blender - a 3D modellingand rendering package. Blender Foundation, Stichting Blender Foundation, Amsterdam, 2018. 5

[4] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In CVPR, pages 770–778, 2016. 5

[5] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In ICML, page 448–456. JMLR.org, 2015. 5

[6] Meiguang Jin, Zhe Hu, and Paolo Favaro. Learning to extract flawless slow motion from blurry videos. In CVPR, June 2019. 2

[7] Meiguang Jin, Givi Meishvili, and Paolo Favaro. Learning to extract a video sequence from a single motion-blurred image. In CVPR, June 2018. 2, 6, 7, 8, 9

[8] Andrej Karpathy, George Toderici, Sanketh Shetty, Thomas Leung, Rahul Sukthankar, and Li Fei-Fei. Large- scale