Image Deblurring with Algorithm Selection and Evaluation for Real-World Images

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***Abstract*— Various techniques for image deblurring have been developed to restore clarity to blurred photographs caused by camera movement. These methods aim to remove blurs and enhance the sharpness of the image, addressing issues such as defocus, motion blur, atmospheric turbulence. In our project, we are tasked with identifying the most effective algorithms for practical applications, including traffic camera images. The evaluation of these algorithms will be based on benchmark scores such as PSNR and SSIM when tested on real blurred photographs. While existing datasets can aid in this evaluation process, it is important to recognize that real-world data may exhibit slight variations. Deblurring techniques can be broadly categorized into blind and non-blind methods, Naf-Net's, Wiener techniques, deep learning approaches, and hybrid methods. Our primary objective is to apply the best algorithm for deblurring photos to achieve remarkably productive results.**

Keywords – ***Deblurring, wiener model, blind deconvolution, hybrid deblurring, Gaussian blur***

I. Introduction

Images can lose clarity due to various factors like subpar camera recording, disruptions, or inadequate lighting during capture, resulting in diminished detail and difficulty in discerning critical information. To address this, deblurring emerges as a valuable technique aimed at minimizing blur and enhancing image quality. Moreover, combating noise interference becomes imperative as it can further degrade image clarity. Deblurring finds application across diverse domains including video object extraction, segmentation, information retrieval, single-image restoration, motion blur detection, and overall image enhancement. Various types of blurs such as defocus and Gaussian blur may occur, necessitating the utilization of blind and non-blind image deconvolution methods to tackle these issues effectively. Additional methodologies encompass deblurring through subspace analysis, the Richardson-Lucy algorithm, noisy image pairings, and Wiener Filtering. Blind deconvolution is employed in scenarios where the problem is poorly defined, requiring educated guesses for the point spread function and clear image. Conversely, non-blind deconvolution relies on known PSF and established deconvolution techniques like Wiener filtering, RL deconvolution, and regularized filter deconvolution to estimate the clear image. The efficacy of image restoration techniques, particularly in picture deblurring and denoising, has witnessed notable advancements. These methods, which can be categorized into inter-block complexities, encounter challenges in dealing with intricate systems.

II. Types of Blurring

A. *Motion blur*

The relative motion that occurs between the camera and the scene during exposure can create blurry images. This blur is considered good if you want to see the direction of motion in a still image. However, due to the rotation and translation of the camera, these artifacts will often appear as the phone in the mobile phone image is held in the hand.

Fig 1. Blur result from lack of focus and lot of details are missing.

Fig 1, Blurring occurs more often in a dark place, when more light is needed and the exposure time is longer. Usually camera shake blur is caused by camera translation, and the blur tends to be all over the image. If the camera's movement is rotated, this will cause additional blur artifacts in areas away from the axis where the rotation occurs. Moving objects form the basis of the third form of blur. If an object moves during exposure, motion blur artifacts will appear in

Fig 2.(a) image of a motion blur , (b) image of rotational blur

the image. Fig2(a), Images are seen and compared with clear images in rotation, translation and object movement. Fig2(b), As can be seen, motion blur caused by camera rotation is stronger than image blur caused by motion blur. In motion blur caused by camera translation, the blur is the same throughout the image[2].

B. *Gaussian Blur*

A Gaussian blur is achieved by convolving an image with a Gaussian function (named after mathematician Carl Friedrich Gauss).Mathematically, applying a Gaussian blur to an image is equivalent to convolving the image with a Gaussian function. The Gaussian function is also known as a two-dimensional Weierstrass transform.

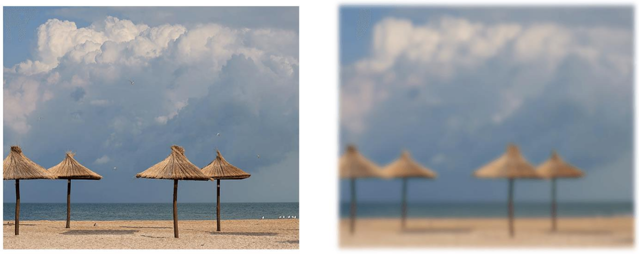

Fig 3.(a)this is original image (b) this is image with gaussian blur effect

The Gaussian function produces concentric circles in two dimensions. These values form a convolution matrix applied to the original image[3]. Each pixel's new value is a weighted average of its neighborhood pixels Boundaries and edges are preserved better than with uniform blurring filters.

$$G(x,y)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Below, Fig 5, you'll see a 2D Gaussian distribution. Notice that there is a peak in the center and the curve flattens out as you move towards the edges [15].

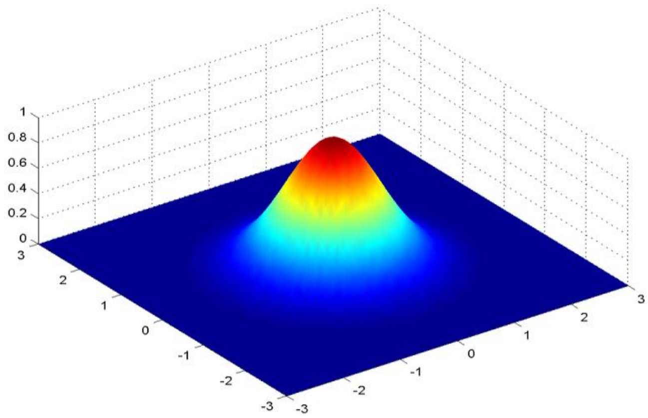

Fig 5. This 2D graph of a gaussian blur

Consider this distribution superimposed on a group of pixels in an image. From this figure, if we take the weighted average of the pixel values and the curve height of the point, it is clearly seen that the pixel in the middle of the group contributes the most to the value benefit. This is basically how Gaussian Blur works.

C. *Defocus blur*

The Defocus is the loss of sharpness resulting from the integration of light at the aperture with the non-zero area (where the light source deviates from the focal plane of the image). The amount of blur seen in an image is a function of the lens aperture, the subject and focus, and the pixel (or grain) size of the camera.

Image blur can be described by a point spread function (PSF). A PSF models how an imaging system captures a single point in the world – it literally describes how a point spreads across an image [4]. An entire image is then made up of a sum of the individual images of every scene point, where each point's image is affected by the PSF associated with that point. For an image to be "in focus" means that one ideally does not want any image blur at a particular depth of the scene. Thus, the PSF should be minimal, i.e., a delta function, where each scene point should correspond only to
one.

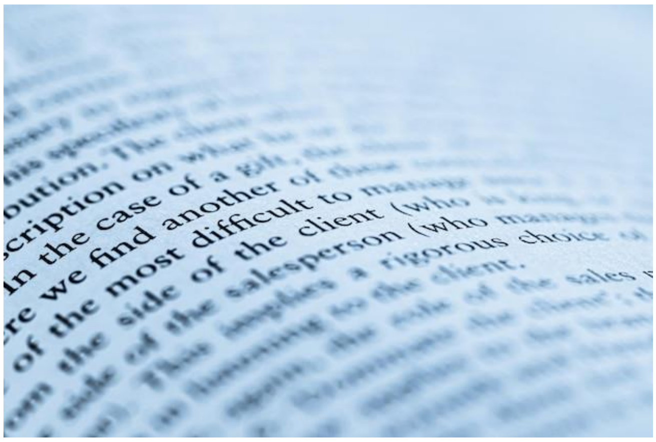

Fig6. This is image of a defocus blur

Text is sharp in the middle of the image, as shown in Fig6, but becomes less sharp as you move to the top or bottom of the image. It is sometimes thought that defocus is good in photography if the depth of field needs to be clear. However, sometimes autofocus may not focus properly, causing the image to mismatch the object in focus.

III. CNN architecture of image deblurring

A. *blind deconvolution*

A Blind deconvolution is a special form of image deconvolution technique proposed by Qi at el. in which the distortion function (blurring kernel) and the original image are estimated simultaneously without a priori from the distorted image. This is especially true when blur is unknown or difficult to model accurately, making the deconvolution process ineffective [6]. one Blind deconvolution techniques usually involve an optimization process that varies the blur estimator and image approximation until convergence. These algorithms usually rely on some assumptions or priorities regarding the image and the blurring kernel to guide the prediction process. Assumptions include sparsity, smoothness, or geometric boundaries of the fuzzy kernel.

B. Non-Blind deconvolution

Non-blind deconvolution techniques are used when blurry faces are known or can be predicted accurately, unlike blind deconvolution techniques where the blurred faces are unknown. This technique uses blur information to enhance or fix bad images. Here are some non-blind deconvolution techniques [14]. Non-blind methods are generally easier to use and require less effort than blind deconvolution methods. However, they require accurate or fuzzy estimates that may not be available in practice. They may also be sensitive to errors or inaccuracies in the fuzzy estimation process. Non-blind methods include several techniques, including Wiener filtering, the Lucy-Richardson method, and the normalization method [1]. The Lucy-Richardson algorithm iteratively estimates the original image by alternating between deconvolving the blurred image with the known point spread function (PSF) and deblurring the result with the PSF.

C. hybrid deblurring

A hybrid architecture may involve combining both traditional image processing techniques and deep learning-based approaches. This could include incorporating traditional deconvolution algorithms with neural network-based methods.

a) *Image Deblurring with CNN*

Image blurring is the process of removing blurry images to make them clearer. CNN-based modeling is more efficient than traditional methods, and most of these methods use repeated inputs to improve the model [5]. For example, the Thin Learning approach has the same type of blindsight imaging using a multi-level neural network and a set of negative functions to optimize the process. The goal of training is to minimize the difference between the deblurred image produced by the CNN and the corresponding smart image. Common loss functions used in image blurring processes include mean square error (MSE), pattern similarity measure (SSIM), or misdetection based on image representation extracted from pre-trained systems such as VGG or ResNet.

b) geometric transformations

Visual processing can play an important role in hybrid architectures for computer vision tasks such as image processing or image deblurring. Visual transformation, also known as image transformation or geometric transformation, involves changing the image in some way to achieve a specific goal [13]. These changes may include operations such as rotation, measurement, translation, thought transfer, etc. Visual transformation can be used as a preliminary step to prepare the input image before feeding it into the blurring model. Visual transformation can be used to remove distracting features from the input image before passing it to the blur model. Techniques such as edge detection, angle detection, or inconsistency filtering (SIFT) can be used to identify key features in the image that are important for deblurring.

IV. ANALYSIS AND APPROACH

Using datasets like GOPRO,IMAGE NET ,Celeb A and others, we analyse and evaluate the top de-blurring algorithmic strategies and sample outcomes are shown in Fig 3.1. After evaluating them, we put them to the test once again using actual datasets. Now, we have utilized the best algorithm that was filtered from the actual dataset to deblur our blurry image.

Fig 6.1 Input Image(Blurred image)

Fig6.2. DAE Fig6.3. Nafnet

Fig6.4.wiener blind

A. DAE

One way is to use convolution techniques designed specifically for image data in the DAE architecture. The training process usually optimizes the loss function based on the difference between the reconstructed image and the original image. Deep-sea researchers are constantly improving blurring techniques. Combining DAEs with other architectures such as Generative Adversarial Networks (GANs) can lead to better results. They excel at tasks such as size reduction and removal, making them useful tools in many applications, including image deblurring. This part of DAE takes the input data (i.e. blurry images) and puts it into a low-level representation that preserves important features [8]. Encoders usually have several layers of reduction that force the network to identify the most important information. While DAEs are good at simple tasks like image deblurring, they can struggle with complex problems or data with noisy patterns. For this case, more innovative models such as convolutional DAEs (CDAEs) or DAEs combined with neural networks (GANs) will be needed.

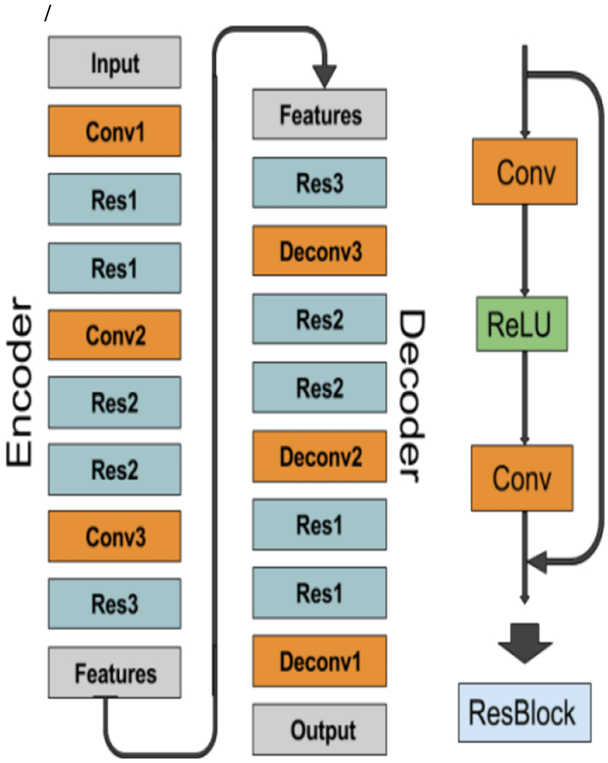

Fig 7. Deep Auto Encoder (DAE's) architecture

B. Wiener blind filtering

The Wiener filter is an MSE-like linear filter suitable for images whose quality is degraded due to added noise and blur. Calculation of the Wiener filter requires the assumption that the signal and noise processes are second-order stationary (in the sense of stochastic processes) [10].

$$\hat{X}(f) = G(f)Y(f)$$

Wiener filter is generally used in the frequency range. Given a distorted image x (n, m), discrete Fourier transform (DFT) is used to obtain X (u, v). Estimate the original image spectrum by multiplying Y (u, v) by the Wiener filter G (u, v)

$$G(f) = \frac{H^*(f)S(f)}{|H(f)|^2 S(f) + N(f)}$$

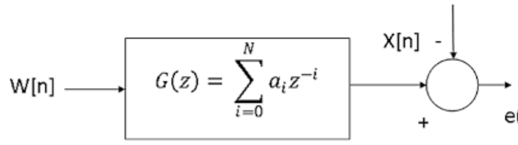

Fig 3.3 An input signal w[n] is convolved with the Wiener filter g[n] and the result is compared to a reference signal s[n] to obtain the filtering error e[n].

During testing, it was found that the proposed network achieved good performance not only with the data measured by GoPro, but also with two new data, which is real-life dataset.

C. Richardson-Lucy Deconvolution

Lucy-Richardson algorithm for image deblurring. It can be used effectively when the source function PSF (fuzzy operator) is known but there is little or no information about the noise[6]. It recovers blur and noise by iterating, accelerating, and fading the Lucy-Richardson algorithms.

The RL algorithm is equipped with the PSF h information and obtains o from observation i by multiplying the potential distribution (3)2 by o. A multivariate algorithm can be used to minimize the log function p (i | o) or an RL algorithm can be developed using the expectation maximization (EM) method [19]. Let's give a brief summary of the second idea. To reduce log p (i | o), J (i | o) must be reduced [9].

$$J_1(o) = \sum_{\mathbf{s}} \left(-i(\mathbf{s}) \log\left[(o * h)(\mathbf{s})\right] + (o * h)(\mathbf{s})\right)$$

After estimation, kernel deconvolution can be performed using Wiener filtering. The Wiener filter minimizes the MSE (Mean Square Error) of expected and predicted processes [12]. Our conditions MSE must ensure that: There is no connection between noise and the original image. The average value of the noise or constant should be zero or close to zero. Prediction is linearly related to visual distortion. In terms of speech, the Wiener filter is less noisy.

Models	SSIM	PNSR
Wiener Filter	**0.950**	**31.05**
Richardson-Lucy	0.910	29.10
NAFNet's	0.920	29.80
DeblurGAN_v2	0.845	26.55
DAE	0.850	27.10

Table 8. Comparison of effectiveness and accuracy using the Gopro test dataset

V. EVALUATION

Real-world images often exhibit various types of distortion, such as noise, blurriness, and compression, as seen in the CCTV images shown in Figures 10.1. This article specifically solve the problem of blurring and proposes the use of algorithms to remove blurring in television recording systems. After analyzing the algorithms shown in Table 8 using GoPro test data and comparing the efficiency and effectiveness, it was found that the Wiener algorithm leads to a better PSNR and gives better images. As a result, the image of the real object disappears the blurring using the Wiener process as shown in figures 1 and 2. 9.1 and 10.1 respectively.

Fig9.1 .input1 real-world image

Fig 9.2 . output1 real-world image

However, it may struggle with complex blur types or non-stationary noise. We did lot of research comparing wiener based methods with other deblurring algorithms to get conclusion of their accuracy [11]. In research we experienced other algorithms such as Naf-Net's values(PSNR and SSIM) are near to wiener model but not good as wiener model. We can use wiener model for CCTV image deblurring with better quality as we can see in Fig 10.2 .In further, we look after the challenges focus on upgrading accuracy and robustness in wiener model.

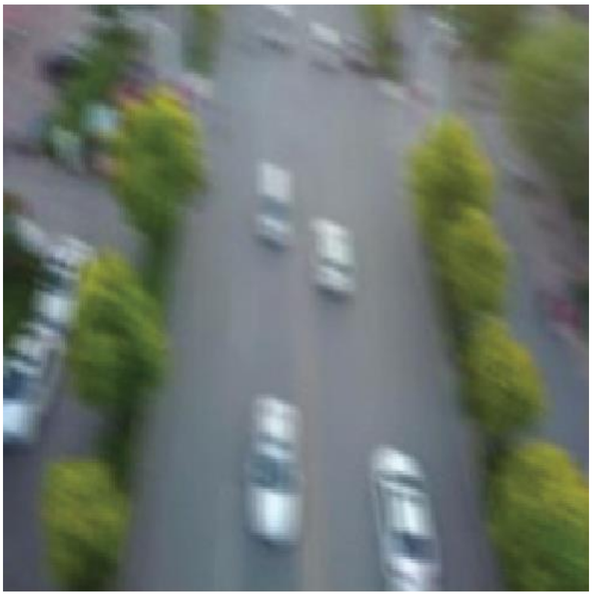

Fig 10.1. Input 2 cc-cam image

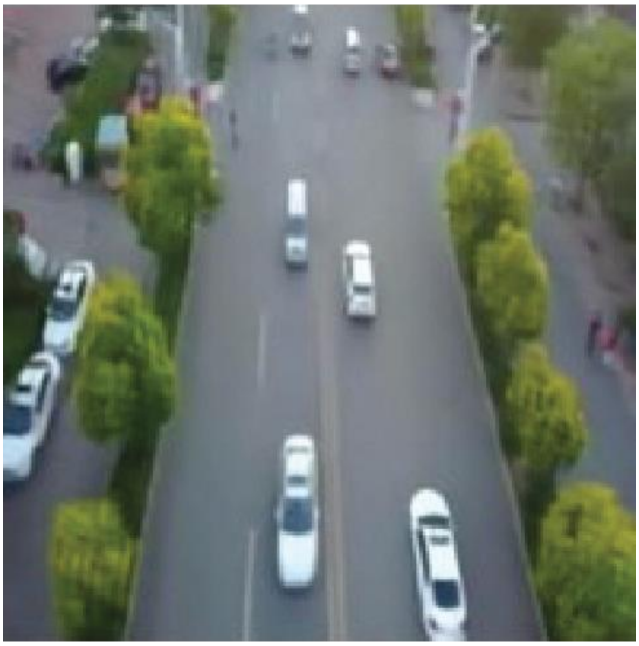

Fig 10.2. Output 2 cc-cam image

VI. CONCLUSION

Choose the best blurring algorithm using several data sets, and then tested the filtering process again using real data. Our images are deblurred using the best techniques. There are many ways to move the project forward. Rich scenes can also be used to perform many tasks such as segmentation, object recognition, object detection, etc. Another application is high-resolution video frame interpolation. We will therefore decide to continue developing our activities to assist future work with better efficiency. Tests of sharpening, optical aberration correction, and camera shake removal on synthetic and real images support our approach and show that shared layers can be adapted to create good models.

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