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Framework for Analyzing the Impact of Blind Deconvolution Algorithm in Image Restoration Process

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Abstract: *The proposed system addresses the problem of blind motion deblurring from a single image, caused by a few moving objects. In such situations only part of the image may be blurred, and the scene consists of layers blurred in different degrees. Most of existing blind deconvolution research concentrates at recovering a single blurring kernel for the entire image. The main aim of the project work is to develop an experimental framework where the input original image will be blurred by means of Gaussian filter and Gaussian noise and then further then further develop a blind deconvolution algorithm and removal of rings using canny edge detection, which develops due to the Gaussian filter and noise. Initially, the original image is degraded using the Degradation Model. It can be done by Gaussian filter which is a low-pass filter used to blur an image. In the edges of the blurred image, the ringing effect can be detected using Canny Edge Detection method and then it can be removed before restoration process. Blind Deconvolution algorithm is applied to the blurred image. It is possible to renovate the original image without having specific knowledge of degradation filter, additive noise and PSF.*

Keywords: Component, Formatting, Style, Styling, Insert

I. Introduction

Motion blur is the result of the relative motion between the camera and the scene during image exposure time. This includes both camera and scene objects motion. As blurring can significantly degrade the visual quality of images, photographers and camera manufactures are frequently searching for methods to limit the phenomenon. One solution that reduces the degree of blur is to capture images using shorter exposure intervals. This, however, increases the amount of noise in the image, especially in dark scenes. An alternative approach is to try to remove the blur off-line. Blur is usually modeled as a linear convolution of an image with a blurring kernel, also known as the point spread function (or PSF). Image deconvolution is the process of recovering the unknown image from its blurred version, given a blurring kernel. In most situations, however, the blurring kernel is unknown as well, and the task also requires the estimation of the underlying blurring kernel. Such a process is usually referred to as blind deconvolution. Most of the existing blind deconvolution research concentrates at recovering a single blurring kernel for the entire image. While the uniform blur assumption is valid for a restricted set of camera motions, it's usually far from being satisfying when the scene contains several objects moving independently. Existing deblurring methods which handle different motions usually rely on multiple frames. In this work, however, we would like to address blind multiple motions deblurring using a single frame. The problem description of the proposed system is to restore a degraded image used for blurring a given image with Gaussian filter and Gaussian noise then further to find the ring effect using canny edge detection then deblurring the image using blind deconvolution algorithm which is effectively used when no information about the distortion (blurring and noise) is known. In image processing and applied mathematics, blind deconvolution is a deconvolution technique that permits recovery of the target scene from a single or set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF). Regular linear and non-linear deconvolution techniques utilize a known PSF. For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed. Researchers have been studying blind deconvolution methods for several decades, and have approached the problem from different directions. The objectives of the proposed system are following: a) To take an input of image, add noise to it and create a blur image for input. b) To consider Gaussian noise to create a degraded image (blur Image). c) Design an algorithm for blurring parameter. d) Implement canny edge detector e) Design blind deconvolution algorithm and f) Design restoration technique.

II. Related Work

Nasonov and Krylov [1] presented the method a new adaptive full reference for quality measurement of image deblurring algorithms is based on the analysis of basic edges sharp edges which are distant from another edges. Amir Beck and Marc Teboulle [2] presented a new fast iterative shrinkage-thresholding algorithm (FISTA) which preserves the computational simplicity of ISTA but with a global rate of convergence which is proven to be significantly better, both theoretically and practically.

Stefan Kindermann et.al [3] investigates the use of regularization functionals with nonlocal correlation terms for the problem of image denoising and image deblurring. JIAN-FENG et.al [4] proposed a method for image deblurring in tight frame domains. It is reduced to finding a sparse solution of a system of linear equations whose coefficient matrix is rectangular. Serena Morigi et.al [5] investigates the use of Cascadic multiresolution methods for image deblurring. Iterations with a conjugate gradient-type method are carried out on each level, and terminated by a stopping rule based on the discrepancy principle. Diana M. Sima [6] presented the new regularization techniques in linear model fitting were focused on the total least square's estimation framework. Thomas SERAFINI et.al [7] presented a new GPU implementation of a recent gradient projection method for edge-preserving removal of Poisson noise. Aram Danielyan et.al [8] presented the analysis/synthesis frames for BM3D image modelling and uses them to develop novel recursive deblurring algorithm based on the augmented LaGrange technique. Yilun Wang et.al [9] analysed and tests an alternating minimization algorithm for recovering images from blurry and noisy observations with total variation (TV) regularization. Dalong Li et.al [10] described an algorithm for the restoration of a noisy blurred image based on support vector regression. The blind image deconvolution was formulated as a machine learning problem.

III. Existing System

The previous research work has been done on:

- The existing system consisted of unified variation research on image deblurring using Salt and pepper noise.
- The current research has also discussed about the problem of blind motion deblurring from a single image, caused by a few moving objects. In such situations only part of the image may be blurred, and the scene consists of layers blurred in different degrees.
- Most of the existing blind deconvolution research concentrates at recovering a single blurring kernel for the entire image.
- While the uniform blur assumption is valid for a restricted set of camera motions, it's usually far from being satisfying when the scene contains several objects moving independently.
- Existing deblurring methods which handle different motions usually rely on multiple frames.
- Other approaches to motion deblurring include hardware approaches and using multiple frames to estimate blur.

IV. Proposed System

The main aim of the project work is to develop an experimental framework where the input original image will be blurred by means of Gaussian filter and Gaussian noise and then further then further develop a blind deconvolution algorithm and removal of rings using canny edge detection, which develops due to the Gaussian filter and noise. The proposed system presents a method for blind image deblurring. The method differs from most other existing methods by only imposing weak restrictions on the blurring filter, being able to recover images which have suffered a wide range of degradations. Good estimates of both the image and the blurring operator are reached by initially considering the main image edges. The proposed system consists of following Modules:

1. Creation of degradation model:
2. Implementing canny Edge Detector
3. Applying Blind deconvolution algorithm

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IV. MODULE DESCRIPTION

The module descriptions of the proposed research work are as follows:

4.1 Creation of Degradation Model

In degradation model, the image is blurred using filters and additive noise. Image can be degraded using Gaussian Filter and Gaussian Noise. Gaussian Filter represents the PSF which is a blurring function. The degradation model of the proposed model is created by using following parameters:

1. **Gaussian Filter:** Gaussian filter is used to blur an image using Gaussian function. It requires two parameters such as mean and variance.
2. **Gaussian Noise:** The ability to simulate the behaviour and effects of noise is central to image restoration. Gaussian noise is a white noise with constant mean and variance. The default values of mean and variance are 0 and 0.01 respectively.
3. **Blurring Parameter:** The parameters needed for blurring an image are PSF, Blur length, Blur angle and type of noise. Point Spread Function is a blurring function. When the intensity of the observed point image is spread over several pixels, this is known as PSF. Blur length is the number of pixels by which the image is degraded. It is number of pixel position is shifted from original position. Blur angle is an angle at which the image is degraded. Available types of noise are Gaussian noise, Salt and pepper noise, Poisson noise, Speckle noise which are used for blurring. In this paper, we are using Gaussian noise which is also known as White noise. It requires mean and variance as parameters.

4.2 Implementing Canny Edge Detector

Canny edge detection method finds edges by looking for local maxima of the gradient off (x, y). The gradient is calculated using the derivative of a Gaussian Filter. The ringing effect can be avoided using edge taper function.

4.3 Applying Blind Deconvolution Algorithm

Blind Deconvolution Algorithm can be used effectively when no information of distortion is known. It restores image and PSF simultaneously. This algorithm can be achieved based on Maximum Likelihood Estimation (MLE).

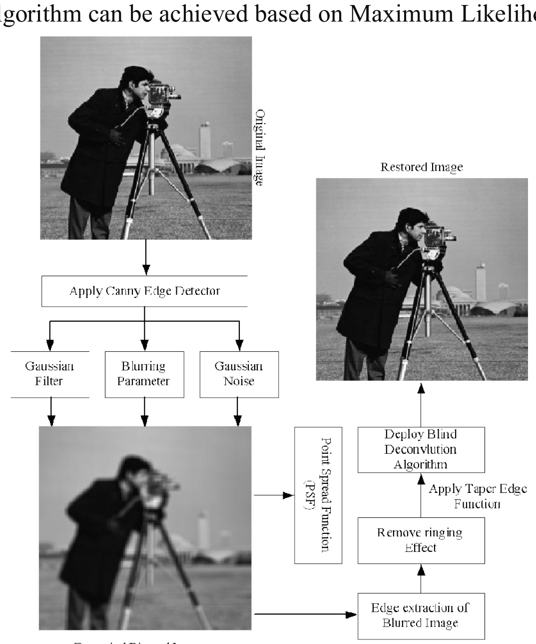

Figure 1: Proposed Architecture

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To determine the size of the PSF, the blurred image and measure the width of a blur (in pixels) around an obviously sharp object is examined. In the sample blurred image, one can measure the blur near the contour of the man's sleeve. Because the size of the PSF is more important than the values it contains, one can typically specify an array of 1's as the initial PSF. The following figure shows a restoration where the initial guess at the PSF is the same size as the PSF that caused the blur. In a real application, one might need to rerun deconvblind, experimenting with PSFs of different sizes, until one achieves a satisfactory result. The restored PSF returned by each deconvolution can also provide valuable hints at the optimal PSF size.

V. Module Description

Figure 2: Original input image

Figure 3: Canny edge detection

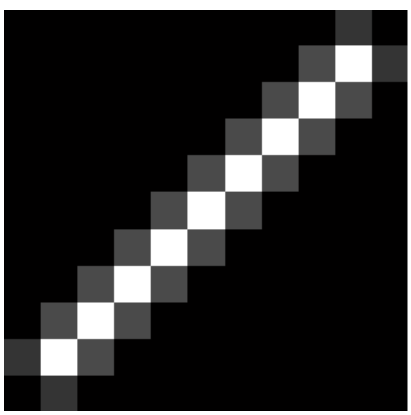

Figure 4: Original Point Spread Function

Figure 5: Blur Image without using deconvolution

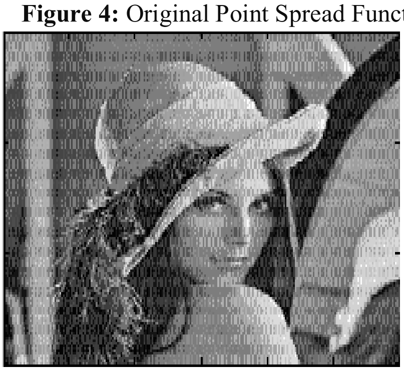

Figure 6: Indexed Lena image

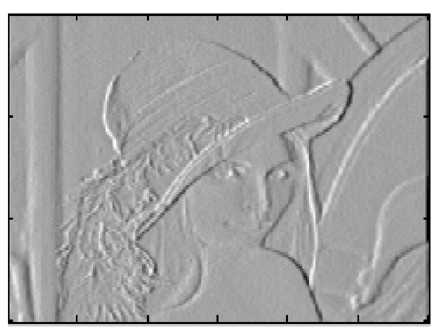

Figure 7: X-Axis Direction edge Detection

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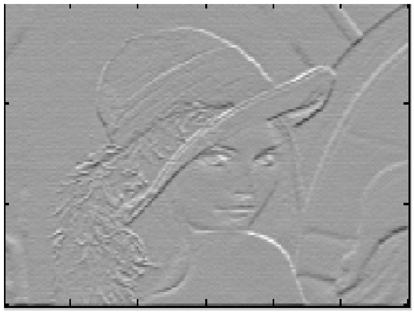

Figure 8: Y-Axis Direction edge Detection

Figure 9: Normalization of Gradient

Figure 10: After Thresholding

Figure 11: After Smoothening

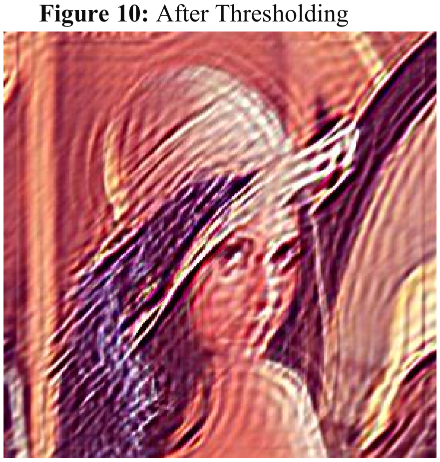

Figure 12: Restored Image

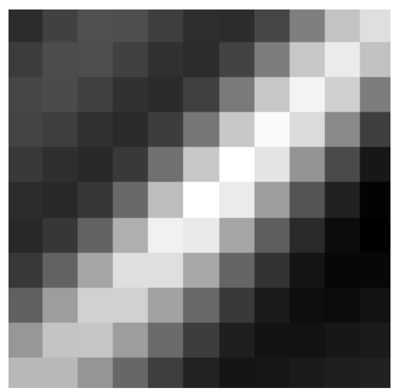

Figure 13: Restored PSF

Figure 14: Newly Deblurred Image

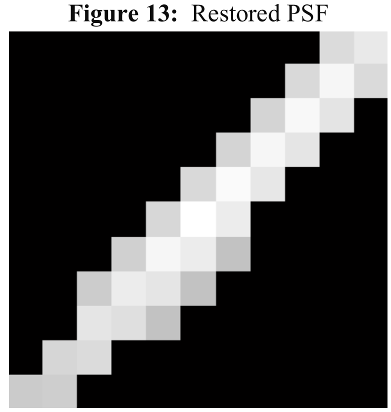

Figure 15: Newly Reconstructed Image

VI. Conclusion

In our conclusion work we have considered a method for blind image deblurring. The method differs from most other existing methods by only imposing weak restrictions on the blurring filter, being able to recover images which have suffered a wide range of degradations. Good estimates of both the image and the blurring operator are reached by initially considering the main image edges. The restoration quality of our method was visually and quantitatively better than those of the other algorithms such as Wiener Filter algorithm, Regularization algorithm and Lucy-Richardson with which it was compared. The advantage of our proposed Blind Deconvolution algorithm is used to deblur the degraded image without prior knowledge of PSF and additive noise. But in other algorithms, we should have the knowledge over the blurring parameters. The future work of this paper is to increase the speed of the deblurring process that is reducing the number of iterations used for deblurring the image for achieving better quality image

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