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A Novel Approach for Image Deblurring

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Abstract- In the area of image processing blur removal is essential step in image quality enhancement .It also has real time applications, therefore it is necessary to have efficient method to remove blur. We have proposed a non linear blur model which simply models low light pixels. In this work we have applied Gaussian kernel instead of Laplacian kernel. The proposed method is developed in such a way that it automatically detects low light pixel from a given blurred image. It also suppress the ringing artifacts. The more accurate results are obtained on problematic and challenging blur images.

Keywords- *kernel ,Gaussian, ,laplacian, pixel, blurred image*

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I. INTRODUCTION

In the area of image processing and computer vision the blur removal is often an essential step in image quality enhancement, object representation, visualization, and many other image processing tasks.In real world applications, image deblurring can be applied in many areas of computer vision and robot vision like digital camera, online games, graphics, traffic monitoring, surveillance- security, defect detection in manufacturing industries, object or obstacle detection in robot vision, medical imaging, army etc.Image deblurring is also used toimprove the detection quality of image that deals with detecting instances of objects of a certain class (such as humans, buildings, tree, road, vehicle *etc*) in digital images and videos.In our daily life, new video cameras such as webcam, infrared camera, cctv camera and other security cameras are installed all around the world for surveillance. This results into development of many intelligent image or video analysis that are used for estimating moving objects.

Blur removal is an important aspect of visual perception and is a technique to improve the visualization power of interesting region or whole image. Generally, humans are able to detect various objects such as trees, vehicle, road, *etc* in background scene. The contrast between the brain and the computer in their capacity to perform visual detection and classification of different stationary or non-stationary object in the scene [1, 2]. This detection task can be formulated as enhancement of detection quality and such problems can be solved in various ways with scientific discipline. There may be many situations where anyone need to recover the sharp version of blurry image so that the fine or sharp details become recognizable through human eyes. But, generally, it is very critical to directly deblur the whole image if scene geometry and camera motion entirely become unknown [1].

As mentioned in the previous section about blur, the blur removal is a phenomenon that becomes perceivable at the time of capturing an image of an object that can be moving faster relative to the shutter of the camera. Such kind of geometric description and the appearance of a scene, and its motion based parameters should be important. A simple example of blurred and deblurred image has shown in Figure 1.1.

According to literature, there exist many problems and issues which causes blur has been generated in image. As interested in rendering or simulating images with motionbased blur[2, 3]. This problem is also called a direct problems since it aims at

Blurred Image	**Deblurred Image**

Figure 1.1: Example of Blurred and Deblurred Image

mimicking the physical process [4]. One may also be interested in the inverse problem, i.e. in the problem of inferring a description of the scene (appearance or geometry) cause of its motion. Such blur is gives motion based blurred images [1, 3, 4, 5, 6]. This problem is called motion deblurring, when the deblurred image is again reconstructed at a resolution higher than the original resolution of input images.Most of the approaches for motion deblurring are based on using a single image as input [1, 2, 4, 5, 6, 7].In literature, many authors have considered blur to be shift-invariant and a single object to be moving in the scene.

Motion-blur is a common distortion of images that becomes perceivable when objects in the scene move at a speed higher than the speed of the shutter of the camera [1]. Given motion blurred images, one may be interested in recovering a sharp or deblurred image of the scene. In order to do so, one needs to recover both the deblurred image and some description of the motion of the scene. For example, one can assume that the motion characterizing a motion-blurred image can be represented by a two-dimensional velocity vector. This assumption, however, is not realistic when multiple objects are simultaneously moving with different speed and/or along different directions. In this case, the complexity of motion cannot be captured by a single two dimensional vector. In order to model a complex motion one can choose a very rich global model, that explains the motion of the entire image, or a very simple model, selected from a small parametric class, together with a segmentation of the regions of the images where the model is satisfied within a prescribed accuracy.

Our goal in this research is to develop and algorithm that automatically remove the deblurring and noise from the image. In the literature, variousstatistical image modeling technique like sparse representation has been used in various image restoration applications. The success of sparse representation owes to the development of the optimization techniques and the fact that natural images are intrinsically sparse in some domains. The image restoration quality largely depends on whether the employed sparse domain can represent well the underlying image. Considering that the contents can vary significantly across different images or different patches in a single image, we propose to learn various sets of bases from a recollected dataset of example image patches, and then, for a given patch to be processed, one set of bases are adaptively selected to characterize the local sparse domain.

This method will show very good results and performs very accurate detection in the video frames.In our research work, we have study various literature of object detection and based on that, we will propose a novel and efficient method which is able to automatically detect the moving objects in video frames.

A. PROBLEM STATEMENT

In this work, the proposed work has suggested a new method that utilizes low ligh tpixels and help in deblurring of low-light images. This work has proposed a non-linear blur model which simply models low light pixels in the dim light sources. This work uses some constraints for evaluating the blur kernel under an optimization technique. The proposed method developed in such a way so that it automatically detects lowlight pixels from given blurred image. According to the proposed experimental results, the suggested methods generates better results with the real-time based problematic and challenging input images whose performance if much better.

In the proposed work, we have applied Gaussian kernel instead of Laplacian because Gaussian kernel models low light pixel very well. The scatterness of such pixels are effectively handled by Gaussian. The deblurring of image using Gaussian parameter and automatically generated variance during runtime.By using multiple low light pixels, we can cumulatively extract a kernel having blur information. This variance depends on the image pixel values while in previous methods this variance has a fixed value i.e. square root of 2. Here, in the proposed work we have removed the dependency on constant parameter i.e. variance. The proposed method has automatically select the variance that tell about the distribution of pixel.

II. PROPOSED ALGORITHM

A.Brief description of working algorithm

In the proposed work, a new framework for deblurring has suggested that properly uses light streaks as main cue for estimating the blur kernel. According to the literature, blur is generated due to light streaks. Here, we have extended a linear blur model by modeling the light streaks where a non-linear model describes accurately about the formation of low-light images which consist of light streaks. The concept of light streak has been developed by Goldstein and Fettal [10].The kernel estimation function takes into account and estimates the light streaks as well as also considers image structures. This work also uses library provided by Hu et. al. 2014.Here, the proposed work develops an algorithm that automatically detects light streaks which is useful i.e. “good” or not useful and these are helpful for estimation of suitable kernel. When the blur kernel has been estimated, the final output image is evaluated by a regularized Richardson-Lucy deconvolution method with outlier handling mechanism that also suppress ringing artifacts.The outlier handling mechanism has been developed by Cho, Wang and Lee [11]. By doing so, the quality of blurred image has been improved.

The proposed method can be understood by the proposed algorithm 1:

III. EXPERIMENTAL SETUP AND PERFORMANCE ANANLYSIS

In the experimental setup section, we have presented experimental results and analysis. Here, all the experiments have done over colored images. In this experimental section, the proposed method has been implemented in MATLAB-2011 (b) and run all experiments on a windows 8.1 (64-bit) operating system having hardware configuration of 1.73 GHz Core i7 CPU and 8 GB RAM. For an image of size

Algorithm 1: Steps for proposed Debluring Method

Input: *Consider blurred image {I(x); where x = (x, y), represent the pixel}.*

Output: *Evaluate deblurred image*

1. **Read one image at a time, I(x).**
2. **Convert RGB pixel and size of image format and in 1-D array i.e. f(x) = I(:);**
3. **Obtain the number of rows and columns from a frame**
4. **Create and initialize one temporary matrices having same sizeas image and normalize the image**
   Image(x,y) = `I(x)/sum(f(:));`
5. **Wrap the boundary using Liu method [12] and Compute the padded image boundaries such that image boundaries are circularly smooth**
   i. Evaluate boundary image contains image intensities at boundaries and subtract boundary points contribution
   ii. Apply DST sine Transform and Compute Eigen values
   iii. Apply inverse sine transform and put solution in inner points; outer points obtained from boundary image.
6. **Whyte et al.'s method is applied for prevent ringing artifacts from saturated pixels.**
   i. Set the parameter true for artifacts and outliers.
7. **Set the initial parameters and apply deconvolution process using Lucy method and here we have applied a Gaussian filter.**
   ii. Set the initial parameters, like mask, no of outliers, strength, etc.
   iii. Apply Gaussian filter
   iv. Apply cho's method to evaluate the weight and normalize weight.
   v. Use imfilter of type same, circular for convolution that has been applied for evaluating the normalized pixel ratio.
   vi. Classify pixel's state(as a property of blur) using the convolved pixel ratio.
8. **Now apply Deconvolution of previously developed results of Gaussian Filter where, The DFT is applied with a fast Fourier transform (FFT) algorithm.**
   i. The inverse fast furrier transform has applied in the deconvolution process.
   ii. This results in Deblurred content of image.
9. **Return the deblurred image**

700x1000, the light streak detection step takes about 8 seconds, and the kernel estimation step takes around 1.2 minutes with the proposed optimized implementation. Due to limited space, this chapter presents some examples that clearly shows the performance of proposed method.

Original Image	**Zhe Hu et. al. 2014**	**Proposed**

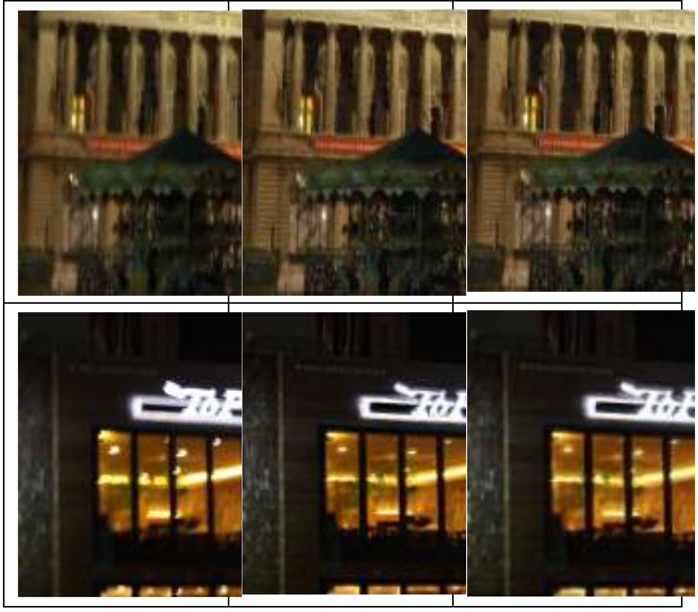

Table 1.1: Qualitative Analysis

The proposed work has been analyzed in terms of mean square error and peak signal to noise ratio.

Themean squared error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. Given a noise-free m×n monochrome image I and its noisy approximation K,
MSE is defined as:

$$MSE=1/mn\{\sum_{i=0}^{m-1} [I(i,j) - K(i,j)]\}^2 \quad (1)$$

These performance evaluation parameters are depicted in Table 1.2, and 4,.3.

Input Image	**Mean Square Error(MSE)**	
	Zhe Hu et. al.	**Proposed**
Building.jpg	9.92E-04	9.93E-04
26.png	8.99E-04	9.14E-04
blurry_2_small.png	9.62E-04	9.61E-04
blurry_7.png	9.79E-04	9.76E-04
DSC0065_small.png	7.95E-04	7.95E-04

Table 1.2 MSE

In statistical modelling the MSE, representing the difference between the actual observations and the observation values predicted by the model, is used to determine the extent to which the model fits the data and whether the removal or some explanatory variables, simplifying the model, is possible without significantly harming the model's predictive ability.

PSNR is simply an approximation in which human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality. The PSNR (in dB) is defined as:

$$PSNR=20.\log_{10}(MAX_1)-10.\log_{10}(MSE) \quad (2)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is 2^B-1.

One more important point is to remember, in case of absence of noise, suppose we have two images I and K, both images are identical, thenthe MSE is zero and in such case the PSNR is infinite.For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space.

Input Image	**PSNR**	
	Zhe Hu et. al.	**Proposed**
Building.jpg	78.1941	78.1973
26.png	78.625	78.6535
blurry_2_small.png	78.3315	78.3382
blurry_7.png	78.2563	78.2695
DSC0065_small.png	79.1587	79.1621

Table 1. 3 Peak-Signal to Noise

From the above results, we have seen the overall performance of proposed method is better as compare to the given Hu's method. The run time performance has shown in Table 1.4. According to the run time analysis, the proposed method performs much better than the existing method.

Input Image	**Total Time**	
	Zhe Hu et. al.	**Proposed**

Building.jpg	141.09681	145.72717
26.png	61.269751	50.587545
blurry_2_small.png	126.57453	125.28638
blurry_7.png	148.72911	143.38133
DSC0065_small.png	257.94914	226.13855

Table 1. 4: Run-time analysis

A. Advantages and Limitations

The speed of this work limits the size of images for which real-time response is reasonable.The main advantage of proposed work is that this method automatically detects the light streaks. Apart from light streaks it also incorporates these light streaks into an optimization process for estimating more accurate blur kernels automatically.

It runs slowly those input images, for those we suggest that if we need to extract a small region inside the image, then the proposed work is suitable for real time.The proposed method sometimes fails for those blurred images that have large intensity value due to incorrect maps of highlight.

IV. CONCLUSION

In this work a novel low light causes streaks based deblurring algorithm has been developed that remove the blur from colored image. In this chapter the proposed deblurring method explicitly models the light streaks for the images captured during low-light. This method detects the light streaks present in the blurred image and then incorporates these streaks into an optimization method. Then estimate a suitable Gaussian based kernel. This method also suppresses the ringing artifacts in non-blind deconvolution step that was generated caused by light streaks. The experimental results clearly presents that the proposed algorithm can obtain more accurate results on the problematic and challenging blurred images and the results are better.

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