iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 Issue: V Month of publication: May 2021

DOI: https://doi.org/10.22214/ijraset.2021.34053

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue V May 2021- Available at www.ijraset.com

Motion Blurred Image Restoration for Text Image

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Abstract: In the process of imaging, the generated image becomes blurred because of the relative movement between the imaging target and the camera. In practical application, this anamorphosis often greatly affect in image identifying and analyzing. So we need some algorithms of inverse process to restore the image. We call the process "motion blurred image restoration". There are several widely used techniques in motion blurred image restoration like direct inverse filter method, Method based on wiener filter and Lucy-richardson non-linear restoration method etc. The application of motion blurred image restoration in various fields as astronomy, military, road transportation, medical images.
Keywords: Motion blurred, text image deblurring, image restoration

I. INTRODUCTION

Image restoration is the process of recovering the original image by removing noise, pixel value errors, out of focus blurring or camera motion blurring of image. Process to reconstruct the image is called deblurring or restoration.
Image deblurring is an important research direction in the field of computer vision and image processing.
Image restoration can be thought of as the inverse process of image blurring. So before we recover the images, we should build a blurring model, analyzing and estimating the process of image blurring and expressing it with a certain mathematical model.
Input image $f(x, y)$ through the blurring system $H(x, y)$, the output is the blurred image g(x,y) . The process of blurring is usually regarded as the noise pollution. Assuming that noise $n(x, y)$ is additive white noise and $H(x, y)$ is a function of all reasons for blurring.

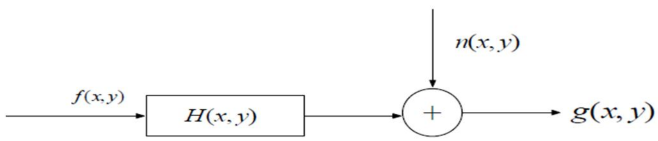

Fig.1 Blurring model [3]

Assuming that noise $n(x, y)$ is additive white noise and $H(x, y)$ is a function of all reasons for blurring. Image blurring model can be described in mathematical expressions:

$$g(x, y) = f(x, y) * h(x, y) + n(x, y)$$

Basic aim of image restoration is deblurring. A recovery system $p(x, y)$ should be designed, in which input is blurring image $g(x, y)$ and output is restoring image $\hat{f}(x, y)$. The restoring image must be closest to the original image.

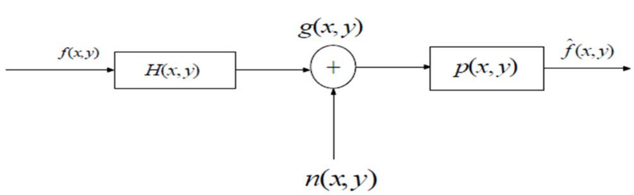

Fig.2 Image blurring and recovery process [3]

The generated image becomes fuzzy because of the relative movement between the imaging target and the camera. So we need some algorithms of inverse process to restore the image. We call the process "motion blurred image restoration".
The methods of motion deblurring can be mainly divided into two categories:
1) Blind restoration methods and
2) Non-blind restoration methods

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The definition of the blind image restoration is that the blur kernel is unknown, or the prior knowledge between the blur kernel and the original image is not completely determined. In the blind restoration methods, the degraded image is used to evaluate both the original clear image and the blur kernel. In The non-blind image restoration assumes that the blur kernel is known. There are several widely used techniques in motion blurred image restoration like direct inverse filter method, Method based on Wiener filter and Conjugate gradient method etc. The application of blurred image restoration in various fields like astronomy, military and road transportation.

II. PROPOSED ALGORITHM

In this section, we present an L0-regularized prior of intensity and gradient for text image deblurring.

A. L0-Regularized Intensity and Gradient Prior

The proposed intensity and gradient prior is based [1] on the observation that text and background regions usually have nearly uniform intensity values in clear images without blurs. Figure 3(b) illustrates that the pixel intensity distribution of a clear text image (figure 3(a)) is peaked at two values (near 0 and 255). For a blurred text image, the pixel intensity distribution is significantly different from that of a clear image. Figure 3(e) shows the histogram of pixel intensities (from a blurred image in (d)) with fewer pixels of value 0 and 255. The reason is that each pixel in a blurred image can be viewed as the weighted sum of a few neighbors of a clear image. Thus, the intensity distribution is squeezed from both ends of the intensity range. As a result, there are fewer pure black pixels (intensity value 0) in a blurred text image than a clear one.

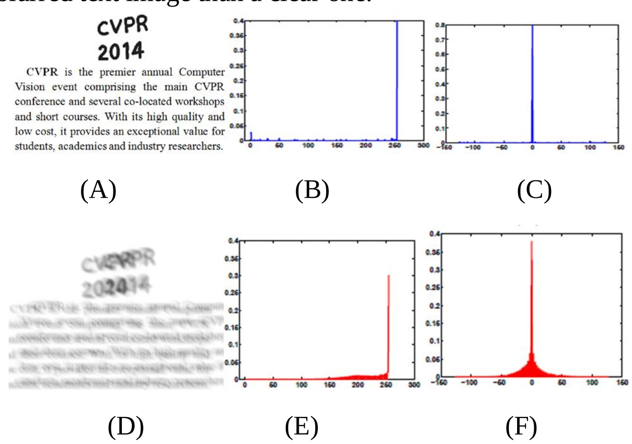

Fig. 3. Intensity and gradient properties of text images[1].(a) a clear text image. (b) Pixel intensity distribution form (a). (c) Distribution of horizontal gradient from (a).(d) A blurred image. (e) Pixel intensity distribution from (d). (f) Distribution of horizontal gradient from (d) .

As a result, there are fewer pure black pixels (intensity value 0) in a blurred text image than a clear one. This intensity property does hold for generic images, and appears more obviously in text images (e.g., document images). For an image x, we describe the property with a regularization term in the proposed model[1],

,P-t.(x) = ‖x,‖-o., (1)

where ||x||0 counts the number of nonzero-intensity pixels in x. With this intensity property, clear and blurred images can be differentiated. We note that, for an image with more white pixels, we can also reverse the pixel intensity by $1-x \rightarrow x$ (for both latent and blurred images) and use the same blur model.

Gradient priors are widely used for image deblurring as they have been shown to be effective in suppressing artifacts [2], [3]. As the intensity values of a clear text image are close to two-tone, the pixel gradients are likely to have a few nonzero values. Figure 3(c) and (f) show the horizontal gradient histograms of a clear text image and the corresponding blurred one. It is clear that the nonzero values of blurred image gradients are denser than those of the clear one. Thus we use a similar L0-regularized prior, ,-t.(∇x), to model image gradients. With the aforementioned regularized priors on intensity and gradient, the prior for text image deblurring is defined by

$P(x)$=σ,P-t.(x)+,P-t.(∇x) (2)

where σ is a weight to balance two priors. Although P(x) is developed based on the assumption that background regions of a text image are uniform, we show this prior can also be applied to deblur complex scenes effectively.

B. Text Image Deblurring via Proposed Prior

A blurred image y can be formulated as the result of a convolution process with a spatially invariant kernel or point spread function,

$$y=x*k+e \qquad (3)$$

where x and e denote the latent image and noise; k is a blur kernel; and * is the convolution operator. Given a blurred image y, we estimate the latent image x and blur kernel k with a regularized formulation based on the proposed prior P(x)[3],

$$\min_{x,k} \|x*k-y\|_2^2+\gamma\|k\|_2^2+\lambda P(x), \qquad (4)$$

where the first term is concerned with image data, and the remaining two terms are constraints for the blur kernel and the latent image, with respective weights, γ as well as λ. We note that we introduce the prior for uniform deblurring.

C. Deblurring Text Images

The deblurring process is modeled as the optimization problem by alternatively solving the latent image x[13],

$$\min_{x} \|x*k-y\|_2^2+\lambda P(x), \qquad (5)$$

and the blur kernel k,

$$\min_{k} \|x*k-y\|_2^2+\gamma\|k\|_2^2 \qquad (6)$$

Two sub-problems are described in the following sections.

1) *Estimating latent image x:* Based on the half-quadratic splitting L0 minimization approach [1], we propose an efficient alternating minimization method to solve this problem[13].

we get,

$$x=\mathcal{F}^{-1}\left(\frac{\overline{\mathcal{F}(k)}\mathcal{F}(y)+\beta\mathcal{F}(u)+\mu F_G}{\overline{\mathcal{F}(k)}\mathcal{F}(k)+\beta+\mu(\sum_{i\in\{h,v\}}\overline{\mathcal{F}(\nabla_i)}\mathcal{F}(\nabla_i))}\right) \qquad (7)$$

Where f(.) And $\mathcal{F}$-1(·)Denote the fourier transform and its inverse transform, respectively; the F¯(.) Is the complex conjugate operator.

2) *Estimating Blur Kernel k:* Given x, (6) is a least squares minimization problem in which a closed-form solution can be computed by FFTs.we estimate the blur kernel k by using (6) & (7) . the solution can be efficiently computed by FFTs [3].

After obtaining k, we set the negative elements to 0, and normalize it so that the sum of its elements is 1. Similar to the state-of-the-art methods, the proposed kernel estimation process is carried out in a coarse-to-fine manner using an image pyramid.

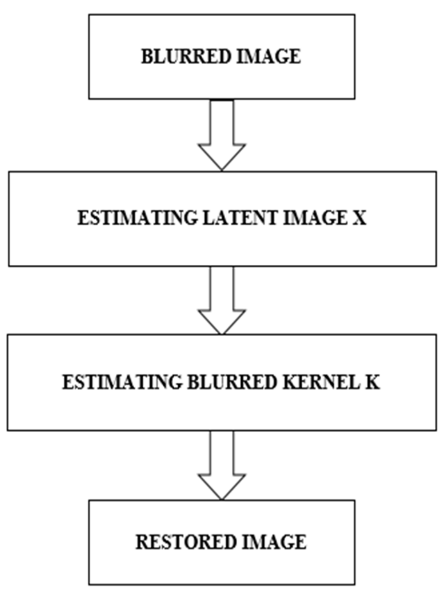

Fig. 4 Basic algorithm for text image restoration

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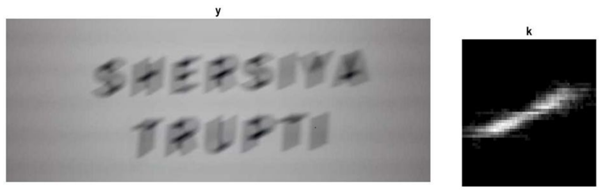
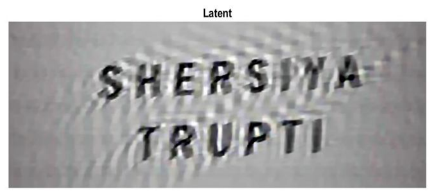
III. EXPERIMENT AND RESULT

Here we used a real blurred image, and this image is blurred during capturing the image. Our input image is recovered by using a proposed algorithm. First we are estimating a blurred kernel because our kernel is unknown. For estimating a kernel, we use different kernel size and peak best result from different sizes. Here our kernel is unknown so our problem is blind deconvolution problem. In blind deconvolution problems we are estimating restored image by using a kernel. In our problem we use the same principle and using the kernel we restored our image.

Fig. 5 is a real blurred image, 5(a) is a blurred image. We are estimating the blurred kernel of fig 5(a) shown in fig 5(b) by using our method. Using a kernel, we restored the image shown in fig 5(c).



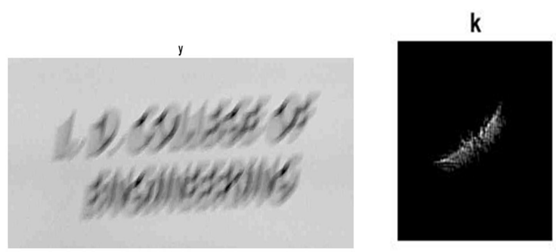
(a) (b)



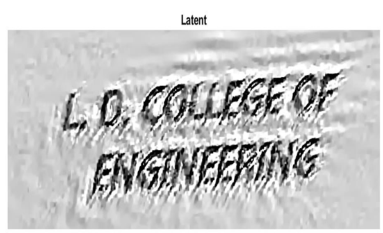
(c)

Fig. 5 (a) blurred image, (b) estimating blurred kernel k and (c) restored image

Using the same method we restored other images shown in fig 6 and fig 7. In both images we used a text image but the font size of text is different. Small size text is hard to recover, but using our algorithm we easily restored small size text.

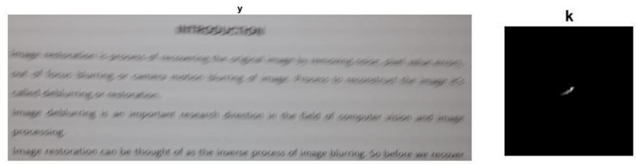


(a) (b)

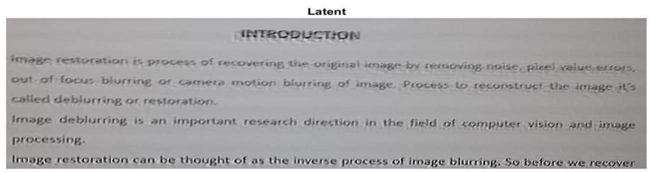


(c)

Fig. 6 (a) blurred image, (b) estimating blurred kernel k and (c) restored image



(a) (b)



(c)

Fig. 7 (a) blurred image, (b) estimating blurred kernel k and (c) restored image

A. Qualitative Results

Quality measurement is the process of measuring distortion in images, by using some metrics that makes a comparison between the original pure image and the distorted image. Image quality measurement is important and helpful for many applications such as in medicine and space images because images can be affected with many factors of distortions. It uses the Normalized Mean Square Error (NMSE),the Structural Similarity Index Measurement (SSIM) and peak noise signal ratio (PNSR) as a metric to measure the quality of distorted images.

Parameter of figure 41

PNSR (dB)	22.7429
SSIM	0.8161
NMSE	0.1447
Image Size (pixel)	294x896
Matlab run time (sec)	340.205324

Parameter of figure 42

PNSR (dB)	21.0223
SSIM	0.7557
NMSE	0.1991
Image size (pixel)	300x896
Matlab run time (sec)	479

Parameter of figure 43

PNSR (dB)	26.3321
SSIM	0.7884
NMSE	0.2265
Image size (pixel)	359*1095
Matlab run time (sec)	703 sec

Parameter of Zhao et al.[11]

PNSR (dB)	20.18
SSIM	0.6012
NMSE	0.0903
Image size (pixel)	306*284
Matlab run time (sec)	112.055

Table 44. Qualitative Results

From Table 44, we can see that the image quality of the proposed method is obviously better than the restoration result using zhao et al. [11].

Value of PNSR is 20.18 db of Zhao et al. [11] and using our method we get PNSR is 26.3321. Thus a higher value of PNSR indicates that the image is of higher quality and vice-versa. A 20 dB or higher value indicates that the image is of good quality. PNSR is an image quality estimator after compression or some modification to the image.

Value of SSIM is 0.6012 of Zhao et al [11] and using our method we SSIM is 0.8161. SSIM (Structural Similarity Index) is a perceptual metric that quantifies image quality degradation* caused by processing such as data compression or by losses in data transmission. It is a full reference metric that requires two images from the same image capture reference image and a processed image. The processed image is typically compressed. SSIM actually measures the perceptual difference between two similar images. It cannot judge which of the two is better: that must be inferred from knowing which is the "original" and which has been subjected to additional processing such as data compression. Cumulative difference between the blurred image and original image is NMSE. Value of NMSE is 0.0903 of Zhao et al [3] and using our method we SSIM is 0.1991.

IV. CONCLUSION

We introduced a new motion deblurring method for text images. While previous methods restored image quality is average because this methods PNSR value is near by 20 to 23 dB, but using proposed method we restored high quality image With PNSR value 26.33 dB. The proposed method is based on the L0 regularization, it can also be effectively applied to non-document text images and low-illumination scenes with saturated regions. The proposed method does not require any complex processing techniques. Our future work focuses on better results and extending the proposed algorithm to restore noise free image.

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