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Image Restoration based on Blur Identification

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Abstract*: It is challenging to take satisfactory photographs in poorly-lit environment using a hand-held camera. With the long exposure time, the image is blurred due to camera shake. Whereas, with short exposure time, the image is dark and noisy. In this project paper we will present a method to improve the quality of given pictures. In particular blind deconvolution will be applied to deblur the images. Blind deconvolution is an indistinct problem and needs to be solved using regularization techniques. The steps involved are: first, an image blur identification index is calculated to evaluate the sharpness of the image. The said index is used in determining whether the following procedure needs to be performed or not. Second, a normalized sparse regularization blind deconvolution technique is used to recover the image. And lastly, we check for quality using various quality assessment algorithms to evaluate the result of recovered image. Experiment result show that the proposed blur identification algorithm and the quality assessment methods are effective in upgrading the efficiency of recovering the image while guarantying a true output.

***Index Terms*: Blur identification metric, Blind restoration, Image quality assessment, Sparse Regularization**

I. INTRODUCTION

The widespread use of electronic devices have made it a necessity for cameras to be an integral part of the mobile phones and PDAs. It is the most a favorable device in everyday use to record information. This condition extensively inspires the advancement of camera-based image processing. While using a camera, we want the recorded image to be a loyal representation of the site that is captured. But most images are more or less blurry. The disorganized camera or the relative motion between the camera and the object can cause the blurring of the image which might affect the contrast, clarity and the preciseness of the image. Taking decent photos under dim lighting is a stressful task. Blurring of an image is difficult to avoid and in most situations and can often wreck a photograph. The image has to encounter many disturbances when going through the stages of storing, processing, compressing, transmitting etc. image deblurring and restoration is therefore necessary in digital image processing.

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In many cases, due to the absence of priori information and the glitches in restoration algorithms the image obtained can have more degradation such as ringing artefacts, which further ruin the image as compared to the original blurred Image. Thus, it is mandatory to check for the level of blurriness before using the restoration algorithms in all practical image processing technique. Hence, we perform blur identification which will find determine the sharpness of the image and choose whether to undergo deblurring technique or not. Also, an image quality assessment needs to be done to obtain a solid output.

There are many articles based on the assessment of image sharpness which can be classified into 3 categories. The first is based on edge detection, where sharpness is evaluated knowing the width of an edge [1]. The local blur is described by assessment of an average edge width which I said to be the assessment metric. The metric and sharpness are inversely proportional. The sharper the image is, the will be the metric. After that another method was proposed for blindly measuring the blur of an image by checking out the sharpness of the sharpest edges in a blurred image [2]. The second category is related to value of pixel of images, i.e. gradient approach [3]. This method is computationally simple but they are also more susceptible to noise as they are solely dependent on change in pixel amplitude. Thus objective image quality assessment value cannot be acquired using this method.

There are two methods to check the quality of the image; the objective and the subjective method. The subjective method is considered costly and time consuming since it requires many observers the result depends on their perception of evaluating the image. The score of all individuals are averaged to get the final score. And thus is impractical for everyday use. The objective method uses automatic algorithms to evaluate the quality without human interference. Objective image quality matrices are classified in different categories depending on the presence of the original reference image:

- Full-reference: where the reference image is available
- Reduced-reference: where only limited information of the image is available and is described by the set of local features.
- No-reference: where the reference image is not available, rather an absolute value is calculated based on few given features of the image.
  This is also known as "blind assessment".

Blind assessment is a challenging task since the unlikeness between image features and impairments are debatable. However, in most cases, the original clear image cannot be acquired in image processing application. Thus, no-reference image quality assessment is crucial.

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Early image quality assessment matrices were based on single attribute such as contrast, sharpness or signal-to-noise ratio of image. Now-a-days various no-reference methods aim to detect particular artifacts.

The analysis of the spread of the edges in images was proposed which was based on a blind blur metric [4]. For JPEG compression, a method is developed through determining relative blur between in-block image samples and zero-crossing rate [5].

In this paper, the proposed no-reference quality assessment metric is based on the assumption of full-reference metric which is called structural similarity (SSIM) [6], the gradient similarity metric was merged into SSIM to acquire a better objective image quality metric.

II. BLIND IMAGE RESTORATION ALGORITHM

The proposed method includes three main stages: blur identification stage, image restoration module and lastly image quality assessment module.

The blur identification module acquires a blur identification metrics which decides whether the image needs to undergo deblurring or not. If not, then the input image itself becomes an output image. In such cases deblurring the image further degrades it and hence is better left alone. Also, the image quality assessment module is included to guarantee an authentic output. Image restoration often leads to other degradation such as ringing artifacts which causes serious reduction in image quality. Thus it is necessary to assess the quality of blurred and deblurred image.

A. Blur Identification

It is desired that blur identification algorithm have low computational complexity and the preciseness in identification be high. In [7] Fergus proposed an image sharpness assessment method based on natural scene statistics to meet these criteria. He called attention to the fact that the gradient distribution of the natural scene image is heavy tailed. While the blurred version of same image does not seem to have this characteristic. Also as per [8] it was observed that the gradient distribution of sharp document image is almost similar to blur natural scene image and it was very different from the gradient distribution of sharp natural scene image.

The [12] logarithmic probability density functions (PDFs) of both sharp natural scene image and Gaussian blurred image was determined in gradient domain, as seen in fig 1. The red solid line denotes the gradient of sharp image whereas the green dashed line is for blurred image. The unlikeness in both the curves is distinctively visible, where the sharp image is wider and heavy tailed, the blurred image is more concentrated. As the blur is increased, the curve gets more and more concentrated. Blurring will reduce the magnitude of the gradient and will eliminate the larger gradients. The objective is to bring the green dashed line on or closer to the red solid line. When this happens we can say the recovered image is closer to the original sharp image and that the deblurring was successful.

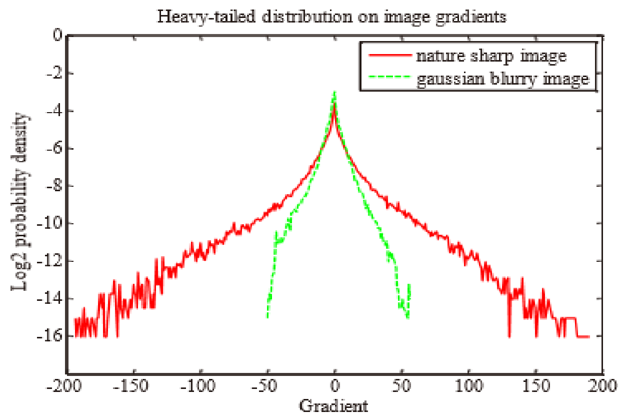

Fig 1: The Distriibution of Gradient Magnitude

The basic idea [9] of our blur identification step is to blur the input image and then to analyze the pattern of variation of adjoining pixels i.e. the pixels of input image and the blurred image are compared. If the input image is a genuinely sharp image then the variation obtained will be quite large. Whereas if the input image itself is blurred then further blurring the image will only converge the pixels to the same grey level and thus variation will be on the fainter degree.

Based on this fact, we are able to calculate the Blur Identification Metrics (BIM) by comparing the variations between neighbouring pixels of the input image and blurred image. So the algorithm involved is:

1. Computing the variations in intensity between the adjoining pixels of the input image.
2. We apply a low pass filter to the input image and again compute the variations between the adjoining pixels.
3. Comparing these variations will give us the value. Maximum among these two values is chosen as BIM value.

Thus, it can be concluded from the comparison that the image is sharp if the high variations were incurred and the slight variation indicates that the input image itself was blurred. The BIM value ranges from 0 to

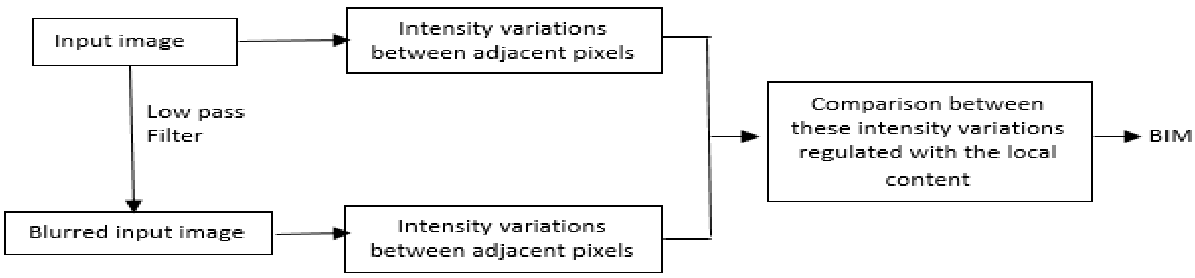

Fig 2: Simplified Flowchart of Blur Identification Metrics (BIM)

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1 which are best and worst quality respectively. This is depicted in the flowchart in fig 1.
After a large number of simulation experiments, we can decide on a threshold T according to the blur restriction that the system can tolerate. If the BIM >T, then the image is said to be blurred and is send further down the ladder to the restoring step. Otherwise, we say that the image is clear enough.

B. Normalised Sparse Regularization blind Restoration Model

For the high-frequency components of an image the regularization function is in the ratio of l_1 norm to l_2 norm l_1/l_2. The simplest interpretation of l_1/l_2 function is that is a normalized version of l_1 [7], making it scale invariant. To penalize these high frequency bands l_1 norm is usually used. Since image noise appears in the high bands, boosting their l_1 norm, minimizing the norm is a way of denoising the image. However, in case of image blur, the blur reduces both l_1 and l_2 norm, but l_2 norm is reduced more than l_1. Hence l_1/l_2 ratio is directly proportional to blurriness. Thus, reducing l_1 norm will remove the blur and will give a sharp image.

The image degradation model of a sharp image x blurred by kernel k with the addition of Gaussian noise n is described as:

$$g = x \otimes k + n \tag{1}$$

The blurring image g is known and our objective is to recover the unknown sharp image x and the blurring kernel k, $\otimes$ is the 2D convolution operator.

1. Blind kernel estimation

Given a blurry and noisy image g, we use discrete filters $\nabla_x = [1,-1]$ and $\nabla_y = [1,-1]^T$ to generate a high frequency version of blurring image $y = [\nabla_x g, \nabla_y g]$. The optimization function [10] for spatially invariant blurring is

$$\min_{x,k} \lambda \|x \otimes k - y\|_2^2 + \frac{\|x\|_1}{\|x\|_2} + \psi \|k\|_1 \tag{2}$$

Which is used to solve the x and k, subject to the constraints that $k \geq 0, \sum_i k_i = 1$. y is concatenation of the two gradient images $\nabla_x g, \nabla_y g$.

Here x is the unknown sharp image, k is the unknown blurring kernel and $\otimes$ is the 2D convolution operator.
(2) consists of 3 terms. The first term is the probability which is set up by the Gaussian noise assumption. The second term is the new l_1 / l_2 regularizer on x which supports scale-invariant sparsity in the reconstruction. As discussed earlier blur increases the l_1/l_2 ratio therefore reducing this regularization term can reach the sharp image. To reduce noise in the kernel, we add l_1 regularization on k. The constraints on k (sum-to-1 and non-negativity) follow from the physical principles of blur formation. The scalar weights λ and ψ control the relative strength of the kernel and image regularization terms.
Initialize x and k, and then update x and k alternately. Only few iterations are carried out in each update to make stable advancement along each of the unknowns.

2. x and k update

$$\min_{x} \lambda \|Kx - y\|_2^2 + \|x\|_1 \tag{3}$$

here K is the blurring kernel.

The algorithm 1 is simple and fast involving only multiplications of matrix K with vector x. This is used as inner iteration. This outer loop then simply re-estimates the weighing on the probability term.

Algorithm 1

Require: operator K ,regularization parameter λ
Require: initial x^0 ,observed image y
Require: threshold t, maximum iterations N
i. For ($j = 0$ to $N-1$) perform
ii. $v = y - tK^T(Kx^j - y)$
iii. $x^{j+1} = S_{t\lambda}(v)$
iv. End for
Return output image x^N

Algorithm 2: the overall x-update algorithm

Require: Blur kernel k from previous k update
Require: Image x^0 from previous x update
Require: Regularization parameter $\lambda = 20$
Require: Maximum outer iterations M ,inner iterations N
Require: Threshold $t = 0.001$
i. For ($j = 0$ to $M-1$) perform
ii. $\lambda' = \lambda \|x^j\|_2$
iii. $x^{j+1} = (k, \lambda', x^j, t, N)$ from algorithm 2
iv. End for
Return updated image x^M

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3. Kernel, k update

$$\min_{k} \lambda \|x \otimes k - y\|_2^2 + \psi \|k\|_1 \tag{4}$$

Subject to the constraints $k \geq 0, \sum_i k_i = 1$.

A vital practical point is that after recovering the kernel at the finest level, we threshold small components of the kernel to zero, thereby increasing robustness to noise. This is similar to other blind deconvolution methods [11].

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4. Multiscale implementation

For large kernels, a high number of x and k updates is needed to converge to a reasonable solution.

To lessen this problem, multiscale estimation of the kernel is performed using a coarse-to-fine kernel estimation process, in a similar manner as in (2).

Size of kernel K determines the number of levels such that at the coarsest the kernel size is 3×3. The input blurry image is downsampled and then the discrete gradients are taken to form the input y each level.

Once a kernel estimate k and sharp gradient image x are determined, they are upsampled to initialize the kernel and sharp image at the next finer level. Bilinear interpolation is used in all resizing operation.

C. No-Reference Quality Assessment Algorithm

Practically, in blind image restoration system, sometimes recovering the image may lead to failure for variety of reasons, which may cause severe image degradation. In order to solve this problem, a no-reference metric to assess the quality of blurring and restored imaged was proposed. The Structural Similarity Metric (SSIM) combines image luminance, contrast and structure.

The SSIM metric [12] is given by:

$$SSIM(x,y)=[l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma} \quad (5)$$

where x, y is the assessed image and the reference image. $l(x,y)$, $c(x,y)$ and $s(x,y)$ is the luminance, contrast and structure similarity of the two images respectively. α,β,γ is the weight of each term.

1. Luminance is defined as

$$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^{\,2}+\mu_y^{\,2}+C_1} \quad (6)$$

where μ_x,μ_y is the mean of luminance corresponding to x, y. C_1 is the constant included to maintain stability when $\mu_x^{\,2}+\mu_y^{\,2}$ is close to zero.

We select $C_1=(K_1L)^2$

where L the dynamic range of pixel values and $K_1<<1$ is a small constant. Similarly, such constants are defined for contrast and structure as well.

2. Contrast is given by

$$c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^{\,2}\sigma_y^{\,2}+C_2} \quad (7)$$

Where σ_x,σ_y is the variance of image x, y respectively.

3. Structure is given as

$$s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3} \quad (8)$$

Where σ_x,σ_y is the variance of image x, y respectively and σ_{xy} is the covariance of two images.

The original SSIM metric uses only the edge information which can handle blurring image. Therefore this metric is improvised by introducing the gradient similarity which describes the edge information.

The Improved Structural Similarity Metric (ISSIM) is given by

$$ISSIM(x,y)=[l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma}[g(x,y)]^{\lambda} \quad (9)$$

where λ is the corresponding weight and $g(x,y)$ is the new defined term which measures the edge similarity of two images and is given by

$$g(x,y)=\frac{2\sum_{i=1}^{m}\sum_{j=1}^{n}g_x(i,j)\,g_y(i,j)+C_4}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(g_x(i,j)\right)^2+\left(g_y(i,j)\right)^2\right]+C_4} \quad (10)$$

where g_x, g_y is the horizontal and vertical gradient images

ISSIM metric requires a reference image if it is to be used in no-reference image quality assessment. The most prominent difference between the sharp and the blurred image are observed in high frequency part of image, i.e. more blurring devotes to less higher frequencies. The reblurred approach is used to measure the quality of single image. If the sharp image is blurred then the quality is significantly affected whereas when a blurred image is reblurred there are no much obvious changes. The two images that are compared here are the input image and the recovered image.

The simplest and the most commonly used full-reference quality metric is mean square error (MSE), which determined by averaging the squared intensity differences of input image and the recovered image pixels, along with the related quantity of peak signal-to-noise ratio(PSNR). These are preferred because of simple calculation, they have clear physical meanings, and are the mathematically convenient in the context of optimization.

III. EXPERIMENTS AND RESULTS

We use MATLAB R2015a to run the various code. Images in the database are taken from various sources.

A.Blind Identification Metric Experiment

The proposed blur identification metric will be studied in the following experiment. From the BIM value obtained for sharp and blurred images, it was observed that as the blur increased the BIM value also increased. In practical application, we simply need to recognize whether an image ought to be reestablished or not which means we only need to determine the threshold according to the requirement. In this work, we processed over 150 images to obtain database. And we decided on threshold to be 0.3 i.2 if the BIM > 0.3 then the image is send to the restoration process otherwise the input image itself becomes our output.

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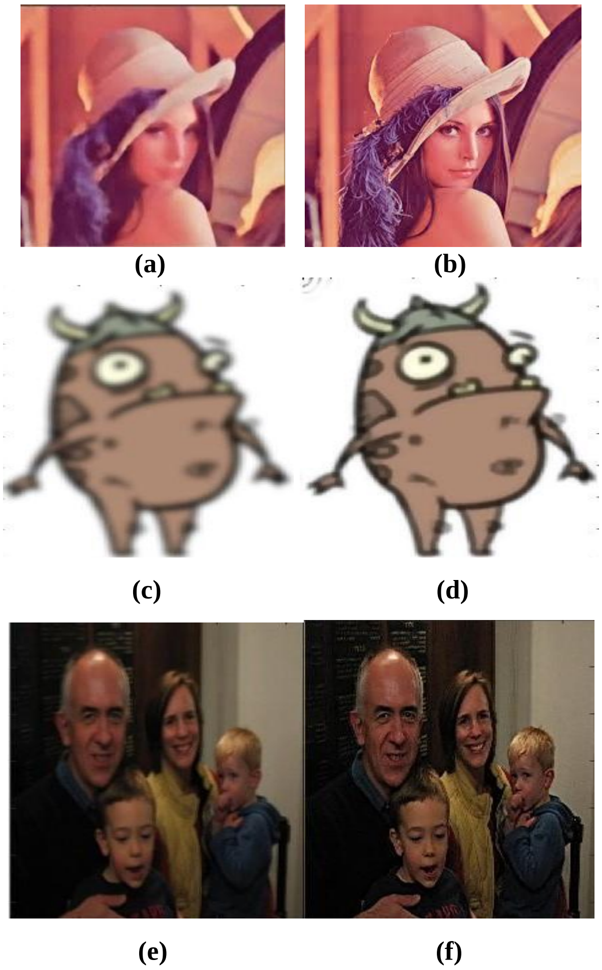

Fig 3:lena: (a),(b); beast: (c),(d); family:(e),(f) .The images (a),(c),(e) are more blurry compared to images (b),(d),(f)

Table1: BIM values of fig.3

	lena	beast	Family
Blurred image	0.4949	0.5696	0.4016
Sharp image	0.3057	0.5018	0.2688

B. Restored Quality Assessment Metrics

The input image after being tested for blur identification will be send to be restored under normalized sparse regularization if the image needs restoration. The result obtained after undergoing sparse regularization showed significant improvement.

The quality of restored image was verified using SSIM, ISSIM metrics.

Fig 3: The input image and the restored images of fishes, family, statue respectively.

Table 2: SSIM, ISSIM, MSE, PSNR

File Name	SSIM	ISSIM	MSE	PSNR
fishes	0.99618	0.98728	0.038424	62.2848
family	0.99958	0.98926	0.003482	72.7124
statue	0.99964	0.98967	0.000172	85.7648

IV. Conclusion

In practical image processing, most of the blind processing algorithm is time-consuming and undependable. In order to solve this problem, a new image blind restoration method based on blur identification and quality assessment of restored image is put forth. The experimental results proved that the proposed blur identification method can distinguish between the blurred and the sharp image. At the same time, the no-reference quality assessment metric gave good results. The SSIM and ISSIM value gave high results indicating that the restored image is quite similar in features to the input image. Also MSE observed was significantly low and the PSNR was quite high. Thus the algorithm proved to give reliable output.

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REFERENCES

1. Wang X, Tian B, Liang C, "Blind image quality assessment for measuring image blur". Proceedings of Conference on Image and Signal Processing, 2008: 467-470.
2. Wang, Xin, et al. "Blind image quality assessment for measuring image blur." Image and Signal Processing, 2008. CISP'08. Congress on. Vol. 1. IEEE, 2008.
3. Batten, Christopher F. Autofocusing and astigmatism correction in the scanning electron microscope. Diss. Faculty of the Department of Engineering, University of Cambridge, 2000.
4. Marziliano, Pina, et al. "A no-reference perceptual blur metric." Image Processing. 2002. Proceedings. 2002 International Conference on. Vol. 3. IEEE, 2002.
5. Wang Z, Sheikh H R, Bovik A C. No-reference perceptual quality assessment of JPEG compressed images. in Proceedings of International Conference on Image Processing, 2002: 477-48Wang, Zhou, et al. "Image quality assessment: from error visibility to structural similarity." IEEE transactions on image processing 13.4 (2004): 600-612.
6. Krishnan, Dilip, Terence Tay, and Rob Fergus. "Blind deconvolution using a normalized sparsity measure." Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. IEEE, 2011.
7. Chen, Xiaogang, et al. "An effective document image deblurring algorithm." Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. IEEE, 2011.
8. Crete, Frederique, et al. "The blur effect: perception and estimation with a new no-reference perceptual blur metric." Electronic Imaging 2007. International Society for Optics and Photonics, 2007.
9. Krishnan, Dilip, Terence Tay, and Rob Fergus. "Blind deconvolution using a normalized sparsity measure." Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. IEEE, 2011.
10. Whyte, Oliver, et al. "Non-Uniform Deblurring for shake images". International journal of computer vision 98.2(2012):168-186.
11. Wang, Zhou, et al. "Image quality assessment: from error visibility to structural similarity." IEEE transactions on image processing 13.4 (2004): 600-612.
12. Lei, Yin, et al. "Image blind restoration based on blur identification and quality assessment of restored image." Control Conference (CCC), 2015 34th Chinese. IEEE, 2015.

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