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IMAGE RESTORATION USING SPARSE REGULARISATION

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ABSTRACT

In this project paper we will present a method to improve the quality of given images. In particular blind deconvolution will be applied to deblur the images. Blind deconvolution is an undefined issue and should be illuminated utilizing regularization methods. The steps involved are: first, an image blur identification index is calculated to assess the sharpness of the image. The aforementioned index is used in determining whether the following procedure should 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 with luminance, contrast and structure 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.

Keywords: Blur identification metric, Blind restoration, Image quality assessment, Sparse Regularization

I. INTRODUCTION

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. 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.

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 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 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. The third category is based on transformation domain which converts image from time domain to frequency or wavelet domain and then extracts the high frequency coefficients to describe the sharpness of image [2].

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.

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 partial information of the image is given. 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 testing undertaking 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.

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 artefacts 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.

The heavy tailed priori is portrayed by magnitude of gradient of images and the range of gradient distribution. The Gradient Magnitude (GM) input image b is calculated as follows:

$$\left.\begin{aligned}
&1.\quad g_x(i,j) = \left|b(i+1,j) - b(i,j)\right| \\
&2.\quad g_y(i,j) = \left|b(i,j+1) - b(i,j)\right| \\
&3.\quad GM = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{\frac{g_x(i,j)^2 + g_y(i,j)^2}{2}}
\end{aligned}\right\} \quad (2)$$

Where g_x and g_y are the gradient of the image in x-direction and y-direction respectively, M and N is the size of the image.

The range of gradient distribution is dependent on the non-zero gradient number. Here the histograms of the above obtained x and y gradient images are determined and the number of greyscale pixels in each histograms are counted; N_x and N_y. Then they are added to form the non-zero gradient number (NGN)

$$NGN = N_x + N_y \quad (3)$$

Knowing both gradient magnitude and non-zero gradient number, the blur identification metric can be calculated. NGN is normalised by the total number of grey scale in two gradient images, say, 512.

Hence, BIM is given by

$$BIM = GM \times \frac{NGN}{512} \quad (4)$$

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

We adopt a typical normalized sparse regularization algorithm for image blind restoration, If the image needs to be restored after blur identification. The process used to restore the blurred image is based on the l_1/l_2 norm constraint, which also is called normalized l_1 regularization constraint [9]. For the sharp image, the regularization term will be minimum.

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

$$g = x \otimes k + n$$

he 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

$$\min_{x,k} \lambda \|x \otimes k - y\|_2^2 + \frac{\|x\|_1}{\|x\|_2} + \psi \|k\|_1 \tag{5}$$

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. (5) consists of 3 terms. The first term is the possibility 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. Since l_1 / l_2 ratio is directly proportional to blurriness, blur increases the l_1 / l_2 ratio therefore reducing this regularization term can reach the sharp image. To noise reduction 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 take care of the relative strength of the kernel and image regularization terms.

Then x and k are initialized and are x and k updated alternately. Only few iterations are carried out in each update to make stable improvement along each of the unknowns.

$$\min_{x} \lambda \|Kx - y\|_2^2 + \|x\|_1 \tag{6}$$

here K is the blurring kernel.

The algorithm 1 is easy 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

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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. $\lambda^{'} = \lambda \left\| x^j \right\|_2$
iii. $x^{j+1} = (k, \lambda^{'}, x^j, t, N)$ from algorithm 2
iv. End for

Return updated image x^M

For updating kernel, k we use,

$$\min_k \lambda \left\| x \otimes k - y \right\|_2^2 + \psi \left\| k \right\|_1 \tag{7}$$

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

A essential 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].

2. Multiscale implementation

When large kernels are used, a high number of x and k updates is needed to converge to a reasonable solution. To limit this issue, multiscale estimation of the kernel is performed using a coarse-to-fine kernel estimation process, in a similar manner as in (5).

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 after that the discrete gradients are taken to shape 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

Recovering the image in blind image restoration system, can sometimes lead to disappointment for variety of reasons, which may cause severe image degradation. In order to solve this problem, a no-reference metric to evaluate 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:

$$SSIM(x, y) = [l\left(x, y\right)]^{\alpha} [c(x, y)]^{\beta} [s(x, y)]^{\gamma} \tag{8}$$

where x, y is the assessed image and the reference image. $l\left(x, y\right)$, $c(x, y)$ 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.

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Luminance , $$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1} \tag{9}$$

Contrast, $$c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2\sigma_y^2+C_2} \tag{10}$$

Structure, $$s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3} \tag{11}$$

where μ_x,μ_y is the mean of luminance corresponding to x,y, σ_x,σ_y is the variance of image x,y and σ_{xy} is the covariance of two images. 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.

The original SSIM metric does not utilize the edge information which can't deal with the blurring image. Therefore, the gradient similarity metrics is introduced in SSIM to describe the edge information which is known is the Improved Structural Similarity Metric (ISSIM) is given by

$$ISSIM(x,y)=[l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma}[g(x,y)]^{\lambda} \tag{12}$$

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

$$g(x,y)=\frac{2\sum_{i=1}^{m}\sum_{j=1}^{n}g_x(i,j)g_y(i,j)+C_4}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(g_x(i,j)\right)^2+\left(g_y(i,j)\right)^2\right]+C_4} \tag{13}$$

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 utilized to gauge the nature of single image. In the event that the sharp picture is blurred then the quality is fundamentally influenced though when a blurred image is reblurred there are no much clear changes. The two pictures that are analysed here are the input picture and the recovered image.

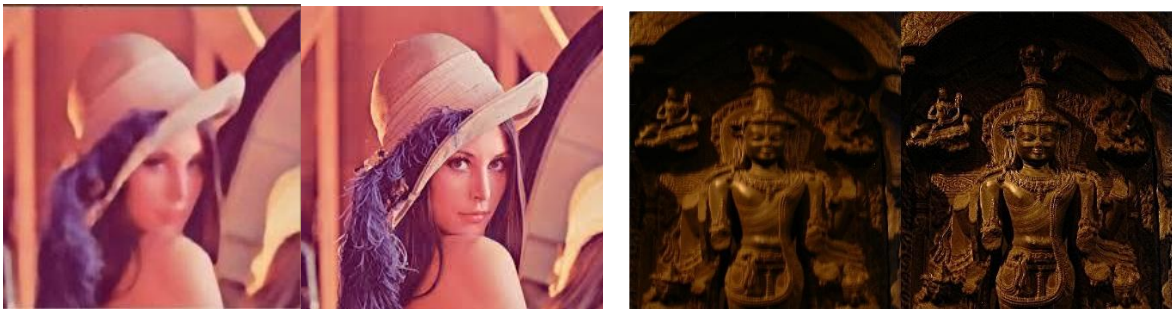
The easiest and the most regularly utilized full-reference quality metric is mean square error (MSE), which is determined by averaging the squared intensity differences of the input image and the recovered image pixels, along with the related quantity of peak signal-to-noise ratio(PSNR). These are preferred because of simple calculation, they have clear physical meanings, and are the mathematically convenient with regards to 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 increasing blur increased the BIM value. In practical application, we simply need to recognize whether an image should be restored or not that is, we only need to determine the threshold according to the requirement. In this work, we processed over 150 images to obtain the database. And we decided on threshold to be 0.3 i.e if the BIM > 0.3 then the image is restored otherwise the input image itself becomes our output.



(a) (b) (c) (d)

Fig 1:lena: (a),(b); statue: (c),(d). The images (a),(c) are more blurry compared to images (b),(d).

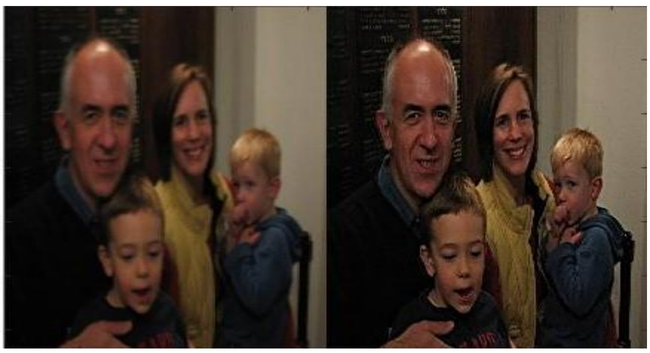
Table1: BIM values of fig.1

	lena	statue
Blurred image	0.4949	0.5696
Sharp image	0.3057	0.2688

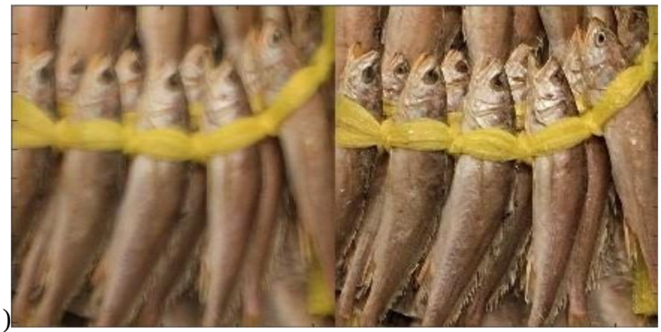
B. Restored Quality Assessment Metrics

The input image after passing through for blur identification will be send the restored process 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, MSE and PSNR.

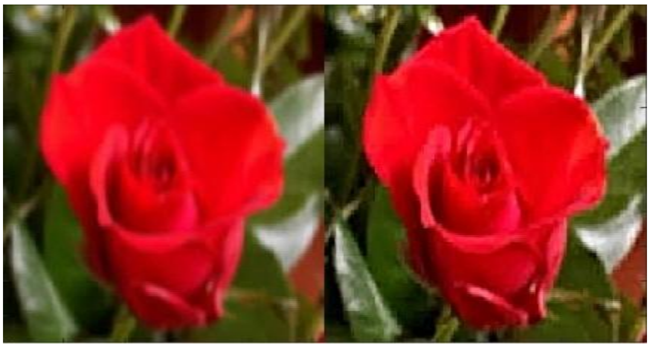


(a) ,(b



)

(c), (d)



(e), (f)

Fig 2: The input image and the restored images of family, fishes and rose respectively.

Table 2: SSIM, ISSIM, MSE, PSNR

File Name	SSIM	ISSIM	MSE	PSNR
family	0.99958	0.98926	0.003482	72.7124
fishes	0.99618	0.98728	0.038424	62.2848
rose	0.99907	0.9942	0.0018414	75.4793

IV. CONCLUSION

In practical image processing, most of the blind processing algorithm are tedious and unpredictable. 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 was observed which was found to be significantly low and the PSNR was quite high. Thus the algorithm proved to give reliable output.

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