Motion Blurred Image Restoration using Moore-Penrose Inverse Approach

Author :Nandni Saxena
Author Affiliation: MTech Scholar (MIST BHOPAL)

Abstract:-Motivated by the problem of restoring blurry images via well developed mathematical methods and techniques based on the inverse procedures in order to obtain an approximation of the original image. By using the proposed algorithm, the resolution of the reconstructed image remains at a very high level, although the main advantage of the method was found on the computational load that will be decreased considerably compare to the othermethods and techniques. The efficiency of the generalized inverse will be compared by the developed simulation outcomes.One of the most intriguing questions in image processing is the problem of recovering the desired or perfect image from a degraded version. In many instances one has the feeling that the degradations in the image are such that relevant information is close to being recognizable, if only the image could be sharpened just a little. Blurring is a form of bandwidth reduction of the image due to imperfect image formation process. .Orthogonal moments have demonstrated significant energy compaction properties that are desirable in the field of image processing, especially in feature and object recognition It can be caused by relative motion between the camera and the original scene, or by optical system, which is out of focus.

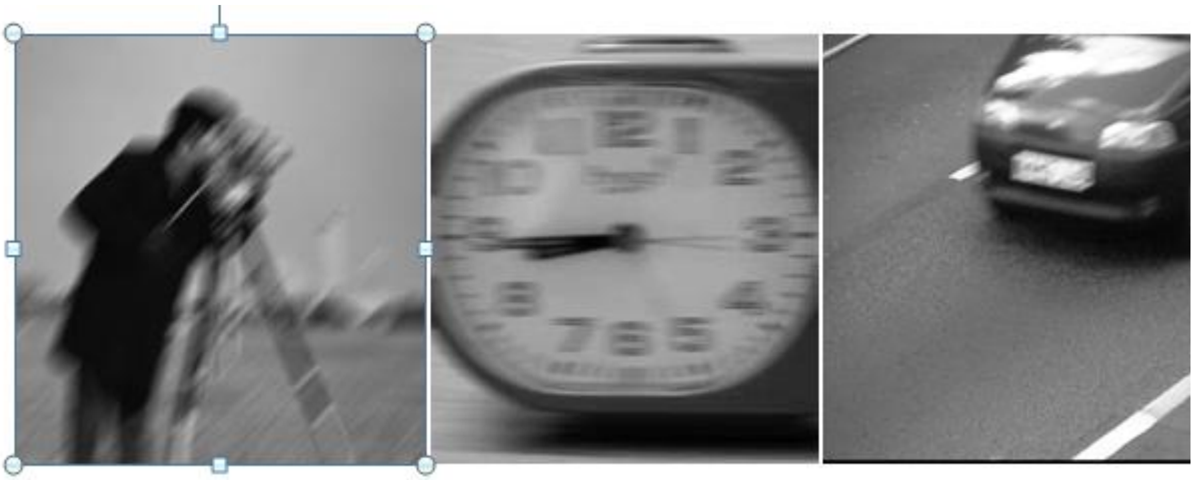
Index Terms:-

I. INTRODUCTION

Image restoration deals with methods to improve the quality of blurred images. It especially deals with the recovery of information that was lost to the human eye during some degradation process.The successful restoration of blurred image requires accurate estimation of PSF parameters. In images, which are blurred by the relative motion between the imaging system and the original scene. Thus, given a motion blurred and noisy image, the task is to identify the point spread function parameters and apply the restoration filter to get an approximation to the original scene.Parameter estimation is based on the observation that image characteristics along the direction of motion are different than the characteristics in other directions. The PSF of motion blur is characterized by two parameters namely, blur direction and blur length. Here need an image which is to restore. Digital imaging devices along with post processing algorithms are very popular in many imaging areas, including consumer photography, microscopy, macro photography,aerial photography, astronomical imaging, medical imaging, etc. However, all these imaging systems suffer from two common distortions, which are blur and noise. Comparedwith noise, which is mainly caused by the sensor and circuitry of a digital camera and could be approximately described through some standard statistical models (e.g. Gaussian distribution, Poisson distribution), blur has more sources and its form can be highly complicated. How to measure and remove various kinds of blur along with noise is a significant problem not only in the image/video restoration area but also in many other applications in the fields of image processing, computer vision, and computational photography.

Nandini Saxena,M.Tech Scholor,Deptt. Of Computer Science & Engineering,Mansarovar Institute Of Science and Technology, Bhopal(M.))

According to its sources, image blur can be generally categorized into four groups: motion blur, lens blur, blur due to transmission medium (e.g. turbulence), and post processing blur (see examples illustrated in Figure **1)**. Either camera or object movement during the exposure period would lead to motion blur. This phenomenon is very common especially for consumer digital cameras. For example, cell phone cameras often cannot be held sufficiently steady, and thus it is easy to generate camera shaking blur. Fast exposure could reduce the blur amount to some degree. factors could make motion blur spatially varying , which makes its estimation and removal highly difficult [1,2].



a) b) c)

Figure 1 a) uniform motion blur caused by camera shaking; (b) non-uniform motion blur caused by object movement; (c) defocus blur in the background;

Incorrect lens setting or limited depth of filed would produce defocus blur.

II. LITERATURE SURVEY

First, let us briefly summarize the relevant existing literature in this area.A commonly used optimization method is through full-reference or reduced-reference metrics [3]. The notion of the generalized inverse of a (square or rectangular) matrix was first introduced by H. Moore in 1920, and again by R. Penrose in 1955, who was apparently unaware of Moore's work. These two definitions are equivalent, (as it was pointed by Rao in 1956) and since then, the generalized inverse of a matrix is also called the Moore-Penrose inverse.Full-reference metrics need a complete reference image, and what they calculate is basically the similarity between the target and reference images. Such measures of similarity include the classical MSE and and the recently introduced Structural Similarity (SSIM) [4]. Reduced-reference metrics require the reference image to be partially available, which is usually in the form of a set of extracted features [4]. However, in most practical applications the reference image is unavailable. Therefore, in applications the (full-reference) quality metrics MSE or SSIM can not be directly used to optimize the parameters of algorithms.In image restoration, as is the case for any estimation problem generally, it can be observed that selecting constructed image into account [12]. An important question for applications is to find a general and algorithmically simple way to compute transpose matrix. There are several methods for computing the Moore-Penrose inverse matrix [2]. Themost common approach uses the Singular Values Decomposition (SVD). This method is very accurate but also time-intensive since it requires a large amount of computational resources, especially in the case of largematrices.

III. PROPOSED METHODOLOGY

Moore-Penrose pseudoinverse of matrices, a concept that generalizes the usual notion of inverse of a square matrix, but that is also applicable to singular square matrices or even to non-square matrices This work introduces a new technique for the removal of blur in an image caused by the uniform linear motion. The method assumes that the linear motion corresponds to a discrete number of pixels and is aligned with the horizontal or vertical sampling.

Given x_{out}, then x_{in} is the deterministic original image that has to be recovered. The relation between these two components in matrix structure is the following :

$$Hx_{in} = x_{out} \tag{1}$$

where H represents a two dimensional ($r \times m$) priori knowledge matrix or it can be estimatedfrom the degraded X-ray image using its Fourier spectrum [10] . The vector xout, is of r

entries, while the vector x_{in} is of $m(= r + n - 1)$ entries, where $m > r$ and n is the length of the blurring process in pixels. The problem consists of solving the underdetermined system of equations (Eq. 1).The generalized inverse approach for a blurred image that has been degraded by a uniform linear motion in the horizontal direction, usually results of camera panning or fast object motion can be expressed as follows,as desribed in Eq. (1)

$$\begin{bmatrix} k_1 & \cdots & k_n & 0\ 0\ 0 \\ \vdots & \ddots & \vdots & 0\ 0\ 0 \\ 0 & \cdots & k_1 & 0\ 0 k_n \end{bmatrix} \begin{bmatrix} x_{in\_1} \\ x_{in\_2} \\ x_{in\_k} \end{bmatrix} = \begin{bmatrix} x_{out\_1} \\ x_{out\_2} \\ x_{out\_k} \end{bmatrix} \quad (2)$$

Where, the index n indicates the linear motion blur in pixels. The element $k_1, \ldots, k_n$ of the matrix are defined as: $k_l = 1/n$ $(1 \le l \le n)$.

$$x_{out}(i) = \frac{1}{n}\sum_{h=0}^{n-1} x_{in}(i+h) \quad (3)$$

that describes an underdetermined system of r simultaneous equations and $m = r + n - 1$ unknowns. The objective is to calculate the original column per column data of the image. For this reason, given each column $[x_{out\_1}, x_{out\_2}, x_{out\_3}, \ldots x_{out\_r}]^T$ of a degraded blurred image x_{out}, Eq. (3) results the corresponding column $[x_{in\_1}, x_{in\_2}, x_{in\_3}, \ldots, x_{in\_m}]^T$ of the original image.

As we have seen, the matrix H is a $r \times m$ matrix, and the rank of H is less or equal to m. Therefore, the linear system of equations is underdetermined. The proper generalized inverse for this case is a left inverse, which is also called a [1,2,4] inverse, in the sense that it needs to satisfy only the three of the four Penrose equations. A left inverse gives the minimum norm solution of this underdetermined linear system, for every $x_{out} \in R(H)$.

The proposed algorithm has been tested on a simulated blurred image produced by applying the matrix H on the original image. This can be represented as

$$x_{out}(i,j) = \frac{1}{n}\sum_{h=0}^{n-1} x_{in}(i, j+h) \quad (4)$$

where $i = 1, \ldots, r$ $j = 1, \ldots, m$ for $m = r + n - 1$, and n is the linear motion blur in pixels. Following the above, and the analysis given in Section 3, there is an infinite number of exact solutions for xin that satisfy the equation $Hx_{in} = x_{out}$, but from proposition 2.2, only one of them minimizes the norm $\| Hx_{in} - x_{out} \|$.

IV. EXPERIMENTAL RESULTS ANALYSIS

The existing and proposed algorithms are anaylized on the image of Figure 1 which are standard images.and resluts are shown in result Table 1 Given Below .

Table: 1 Result Analysis and Comparison of Methods

Image	Evaluation Parameters	Weiner	Lucy Richard-son	Propose Method
Camera Man	PSNR(dB)	123.47	122.6	235.2
	MSE	.004	0.003	000.0
	SNR	118	116.9	229.8
Alarm Clock	PSNR(dB)	124.45	123	245
	MSE	0.013	0.015	0.0089
	SNR	118.73	118.0	239
Moving Car	PSNR(dB)	33.65	30.25	239
	MSE	0.000	00.00	0.0010
	SNR	27.18	23.75	244

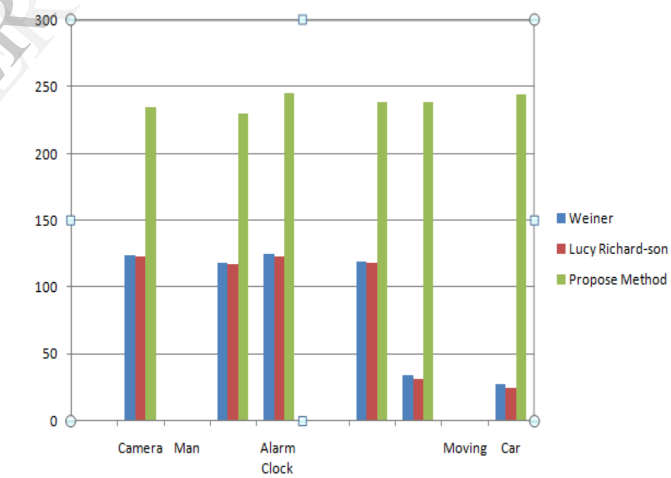


Figure 2: Result Comparison of Methods where Blur length 20 and Blur angle 45 degree.

There are lots of quantitative parameters reported in literature which can be used to compare the image quality. Accordingly we have chosen three such parameters. In this text the de-noising performance, contrast and sharpness enhancement of the image is quantitatively measured by PSNR, MSE and SNR as in below equations.

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$$PSNR \text{ in } dB = 10 \, Log_{10} \left(\frac{255^2}{MSE}\right) \quad (5)$$

$$MSE = \frac{\sum_i \sum_j \{Y(i,j) - \tilde{Y}(i,j)\}^2}{M \times N} \quad (6)$$

Where PSNR stands Peak Signal to Noise Ratio, MSE stands for Mean Square Error, SNR stands for Signal to Noise Ratio is size of the image, Y represents the original image, denotes the denoised image. A Higher PSNR indicates the reconstruction is of higher quality while when the two images are identical.

V. CONCLUSION

In this study, we introduced a novel computational method based on the calculation of the Moore-Penrose inverse of full rank r × m matrix, with particular focus on problems arising in image processing. We are motivated by the problem of restoring blurry and noisy images via well developed mathematical methods and techniques based on the inverse procedures in order to obtain an approximation of the original image. By using the proposed algorithm, the resolution of the reconstructed image remains at a very high level, although the main advantage of the method was found on the computational load that has been decreased considerably compared to the othermethods and techniques. The efficiency of the generalized inverse is evidenced by the presented simulation results.

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