An Efficient Method for Image Restoration from Motion Blur and Additive White Gaussian Denoising Using Richardson Lucy Deconvolution and Fuzzy De-Noising

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Abstract: The proposed system deal with the problem of restoration of images blurred by relative motion between the camera and the object of interest. For correct restoration of the degraded image, it is useful to know the point-spread function (PSF) of the blurring system. It is a straightforward method to restore motion-blurred images given only the blurred image itself. The method first identifies the PSF of the blur and then uses it to restore the blurred image. The blur identification here is based on the concept that image characteristics along the direction of motion are affected mostly by the blur and are different from the characteristics in other directions. By filtering the blurred image, we emphasize the PSF correlation properties at the expense of those of the original image.

Keywords: *Motion Blur, Image Restoration, Image Degradation.*

1. INTRODUCTION

Motion blur and noise are strictly related by the exposure time: photographers, before acquiring pictures of moving objects or dim scenes, always consider whether motion blur may occur and carefully set the exposure time. The tradeoff is between long exposures that reduce the noise at the cost of increasing the blur, and short exposures that reduce the blur at the cost of increasing the noise. Often there is no satisfactory compromise, and the captured image is inevitably too blurry or too noisy.

A long-distance imaging system can be strongly affected by atmospheric turbulence, which randomly changes the refractive index along the optical transmission path, generating geometric distortion (motion), space and time varying blur, and sometimes even motion blur if the exposure time is not sufficiently short. Aside from hardware-based adaptive optics approaches, several signal processing approaches have been proposed to solve this problem. These approaches attempt to restore a single high-quality image from an observed frame sequence distorted by air turbulence.

As with these other works based on videos or image sequences, we work under the assumption that the scene and the image sensor are both static, and that observed motions are due to the air turbulence alone. The imaging process can be modeled as some multi-frame reconstruction approaches first employ a non-rigid image registration technique to register each observed frame with respect to a fixed reference grid, and use the registration parameters to estimate the corresponding motion field for each frame. Unfortunately, the assumption of constant motion during the entire imaging process does not hold for many cases of motion blur. For example, analysis of images taken with small digital cameras shows that consecutive images covering the same scene have different motion blur. In particular, the direction of motion blur is different from one image to another due to trembling of the hand. In the image restoration algorithm included an estimation of the PSF (Point Spread Function) from two images. However, it assumes a pure translation between the images, and uses the location of singularities in the frequency domain which are not stable.

One solution that reduces the degree of blur is to capture images using shorter exposure intervals. This, however, increases the amount of noise in the image, especially in dark scenes. An alternative approach is to try to remove the blur off-line. The problem of restoration of blurred image with complex background and noise reduction has proved unsolved. The blurred part is complex to extract from the complex background in the previous system, and then it is pasted onto a bottom with monochromatic background with multiple noises like additive and specular noises.

Image deconvolution algorithm varies the result and only focus on exposure of rectilinear blur, for which a statistical analysis based methods, produces unsatisfactory results. More specifically, each restoration-error model describes how the expected restoration error of a particular image-deblurring algorithm varies as the blur due to camera motion develops over time along with the PSF trajectory, which we effectively handle by means of statistical descriptors.

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The peculiarity of the proposed methodology is that it simultaneously takes into account the motion blur and additive noises, its interplay with the sensor noise, and the motion randomness. To put our contribution in perspective, let us briefly summarize some of the most important related works, where ad-hoc devices and controlled or customized acquisition strategies are devised to ease the restoration task.

Differently from image stabilization techniques, which counteract/prevent the blur, most computational-photography techniques leverage particular acquisition strategies (or settings) that make the algorithmic inversion of the blurring operator easier. These algorithms can be divided into two classes: the first class consists of algorithms that couple the blurred image with some additional information, while the second class consists of algorithms that tweak the camera acquisition to obtain PSFs that are easier to invert. The first class of algorithms includes, which exploit hybrid imaging systems (provided with two cameras having different resolutions) that are able to measure their own motion during the acquisition.

2. RELATED WORK

In previous works of Giacomo Boracchi and Alessandro Foi the PSF trajectories as random processes and, following a Monte Carlo approach, expresses the restoration performance as the expectation of the restoration error conditioned on some motion-randomness descriptors and on the exposure time. This allows us to coherently encompass various imaging scenarios, including camera shake and uniform (rectilinear) motion, and, for each of these, identify the specific exposure time that maximizes the image quality after deblurring.

The work of Marius Tico, Markku Vehvilainen the exposure times of the two images determines differences in their degradations which are exploited in order to recover the original image of the scene. We formulate the problem as a maximum a posteriori (MAP) estimation based on the degradation models of the two observed images, as well as by imposing an edge-preserving image prior.

The proposed methodology for deriving a statistical model of the performance of a given deblurring algorithm, when used to restore motion blurred images. The blur PSF is then computed from these motion information, and the blur is inverted using the traditional Richardson–Lucy deconvolution. These works focus on camera shake and pair a long-exposure image, which is dominated by blur, with a short-exposure one, which is corrupted by overwhelming noise: the short-exposure image is treated as blur-free, and used for computing the blur PSF. Differently, the algorithm proposed in focuses on rectilinear PSF, and combines several blurred images acquired with different exposure times to compensate the frequencies suppressed by blur in each observation. Algorithms of the second class aim at actively controlling the camera during the acquisition, thus piloting the resulting PSF, so that the blur inversion becomes a well-conditioned problem. In, it is shown that the motion blur can be effectively handled by fluttering the camera shutter during the acquisition, following a coded exposure. Such a coded exposure makes the resulting blur easier to invert.

3. OUR CONTRIBUTION

3.1 Single Image Blind Deconvolution

In image deconvolution, the goal is to estimate an original image f = {f(x, y), x = 1,….,N, y = 1, ….,N} from a observed version g = {g(x,y), x = 1,….,N, y = 1, …,N}, assumed to have been produced according to g(x, y) = f(x,y) * h(x,y) + w(x,y), where h(x, y) is the blur point spread function (PSF), {n(x, y),x = 1, ….,N, y =1,….,N} is a set of independent samples.

Finally, a single image deblurring algorithm is required as a post-process to deconvolve the near-diffraction limited image Z.

The degradation model

$$\mathbf{Z} = \mathbf{F} \otimes \boldsymbol{h} + \boldsymbol{\varepsilon} \tag{1}$$

where ε represents error caused by the process generating the estimate of Z. where ε represents error caused by the process generating the estimate of Z. Such blind deconvolution algorithm can be described generally using the following

$$<\boldsymbol{F}, \hat{\mathbf{h}}> = \underset{\boldsymbol{F}.\boldsymbol{h}}{\arg\min} \; \| \mathbf{Z} - \boldsymbol{h} \otimes \boldsymbol{F} \|^2 + \lambda_1 \boldsymbol{R_f}(\boldsymbol{F}) + \lambda_2 \boldsymbol{R_h}(\boldsymbol{h}), \tag{2}$$

where *Rf* and *Rh* are the regularization terms based on prior knowledge about the latent sharp image *F* and the PSF *h*.

3.2 Fuzzy Image Denoising

The general idea in this method is to take into account the fine details of the image such as edges and color component distances, which will be preserved by the filter. The goal of the first filter is to distinguish between local variations due to image structures such as edges. The goal is accomplished by using Euclidean distances between color components instead of differences between the components as done in most of the existing filters.

The proposed method uses 2-D distances instead of 3-D distances (distance between three color components red, green and blue), that is, the distance between red-green (RG) and red-blue (RB) of the neighborhood centered at (i, j) is used to filter the red component. Similarly, the distance between RG and green-blue (GB) is used to filter the green component and the distance between RB and GB is used to filter the blue component, respectively.

Similarly, fuzzy rules for the green component (using RG and GB couple) and the blue component (using RB and GB couple) can be computed. In the above fuzzy rules DISTANCE represents the Euclidean distance.

DISTANCE (RG, NEIGH(RG)) = [(Ci+k,j+l,1 - Ci,j,1)2 + (Ci+k,j+l,2 - Ci,j,2)2]1/2
(3)

In the proposed approach, the membership function SMALL has been modified which incorporates a two-sided composite of two different Gaussian curves. The Gaussian function depends on two parameters σ and c as given by

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (4)$$

The membership function *gauss2mf* (supported by MATLAB) is a combination of two of these two parameters. The first function, specified by _1 and c1, determines the shape of the leftmost curve. The second function specified by _2 and c2 determines the shape of the right-most curve.

4. IMPLEMENTATION

Various methods for removing or preventing the motion blur degradation have been proposed. The existent solutions can be divided in two categories based on whether they are aiming to correct or to prevent the motion blur degradation. In the first category are those solutions that are aiming for restoring a single image shot captured during the exposure time. This is actually the classical case of image capturing, where the acquired image is typically corrupted by motion blur, caused by the motion that have taken place during the exposure time. If the point spread function (PSF) of the motion blur is known then the original image could be restored, up to some level of accuracy (determined by the lost spatial frequencies), by applying an image restoration approach. However, the main difficulty is that in most practical situations the motion blur PSF is not known.

Moreover, since the PSF depends of the camera motion during the exposure time, it is rather difficult to establish a universal model for the blur process. The lack of knowledge about the blur PSF suggests the use of blind deconvolution approaches in order to restore the motion blurred images. Unfortunately, most of these methods rely on rather simple motion models, e.g. linear constant speed motion, and hence their potential use in consumer products is rather limited. Measurements of the camera motion during the exposure time could help in estimating the motion blur PSF and eventually to restore the original image of the scene.

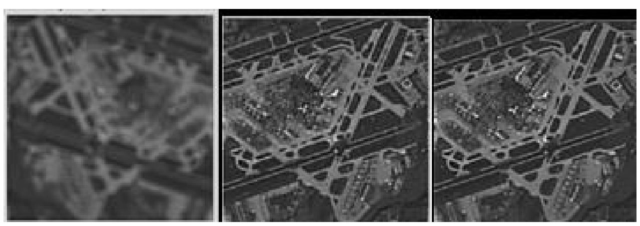
To demonstrate the process of deconvolving in the entire image with the same kernel damages the unblurred parts. One obvious solution is to divide the image into regions and match a separate blur kernel to each region. While likelihood measure based on a big window is more reliable, such a window might cover regions from different blurring layers. Another alternative is to break the image into segments using an unsupervised segmentation algorithm, and match a kernel to each segment. The facts that blur changes the derivatives a distribution also suggests that it might be captured as a kind of texture cue. Therefore, it’s particularly interesting to try segmenting the image using texture affinities. However, as this is an unsupervised segmentation process which does not take into account the grouping goal, it’s hard to expect it to yield exactly the blurred layers. The output over-segments blur layers, while merging parts of blurred and unblurred objects.To demonstrate the process of deconvolving in the entire image with the same kernel damages the unblurred parts. One obvious solution is to divide the image into regions and match a separate blur kernel to each region.

5. RESULTS

The proposed methodology for deriving a statistical model of the performance of a given deblurring algorithm, when used to restore motion blurred images. Differently from our earlier work on rectilinear blur , it do not enforce any analytical formulation for the trajectories generating the motion-blur PSFs and we deal with random motion, which is effectively handled by means of statistical descriptors of the PSF.

The extensive experiments on camera raw images investigated the blur/noise tradeoff that rules the restoration performance in presence of motion blur, and show that the computed restoration-error models provide estimates that are coherent with the results on real data.

In practice these models, combined with functions expressing how the PSF descriptors vary w.r.t. the exposure times, provide concrete guidelines for predicting the exposure time that maximizes the quality of the image restored by the corresponding algorithm. The outcomes of the restoration error models obtained from three different deconvolution algorithms (namely the anisotropic LPA-ICI deconvolution, the deconvolution using sparse natural image priors, and the Richardson– Lucy deconvolution), agree with the results, with the acquisition strategies followed in the practice to cope with camera shake, and with an extensive experimental evaluation performed on camera raw images.



a) Figure 5.1 a) Blurred and Noisy Image b) Deblurred Noisy Image and c) Fuzzy Denoised Image

5.1 Image Errors Measurements

The comparison of errors measurement of image is to develop quantitative measures that can automatically predict perceived image quality. The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

- The signal-to-noise ratio (SNR) is used in imaging as a physical measure of the sensitivity of a (digital or film) imaging system.
- PSNR is an approximation to human perception of reconstruction quality. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.
- In statistics, the mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. It measures the average of the squares of the "errors." The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator.
- Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root-mean-square error or root-mean-square deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the

Table 1: Experimental Results

Image Error Measurements	Noisy Image Values	DWT Algorithm	Laplacian Algorithm	Proposed Denoise and Deblur Algorithm
ISNR	3.864	3.984	4.038	4.565
SNR	20.815	20.944	20.549	21.998
PSNR	29.977	29.994	30.0873	31.560
MSE	65.364	63.501	64.071	56.163
RMSE	8.0848	7.982	7.839	7.491
MAE	5.498	5.387	5.257	5.001
MAX	123.832	120.739	119.490	104.789

The values shows that the consideration of proposed values is achieved the better performance comparing to the original image and the other method. It shows the improvisation of image quality.

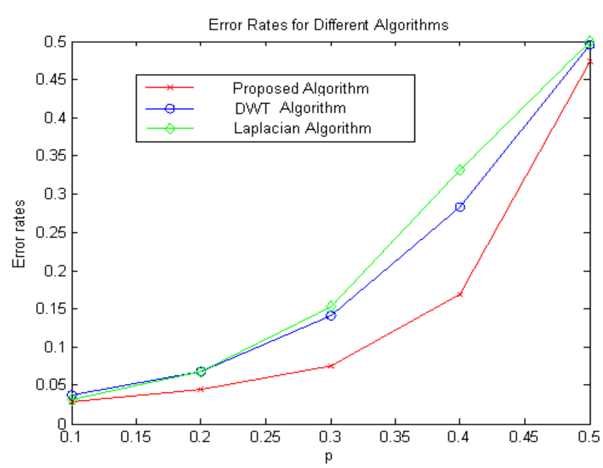


Figure 2: Comparison of errors measurements

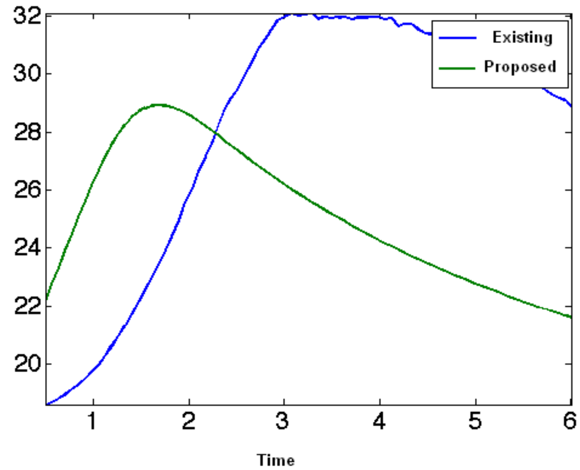


Figure 3: Comparison of processing time of existing and proposed system

To demonstrate the significant improvement arising from our modified algorithm, comparably it reduces the processing time. First, it restores the image applying the algorithm in a straightforward manner, estimating the noise using the standard parameters that were optimized for the Gaussian case. Second, tune the parameters, in order to compensate to the wrong noise model. In existing Denoising Completed in 32.19 seconds and De Blurring completed in 8.22 seconds on same hand in proposed it achieves the result of Denoising image in 22.16 seconds and De Blurring image in 6.68 seconds.

6. CONCLUSION

Our image restoration process takes into account of motion blur by allowing some pixels to be reconstructed from a single image, but a full treatment of deconvolution remains an open challenge. Our solution uses two exposures in order to cover the full velocity range while minimizing the time overhead and additive noise penalty. According to experiments on both synthetically generated observation and on camera raw data, the estimated optimal exposure times correspond to observations that are corrupted by noise levels that are far from being negligible. The comprehensive study of solutions relying on an arbitrary number of exposures is, however, an important open question which requires careful modeling of the motion blur and noise.

7. FUTURE WORK

Our solution uses two exposures in order to cover the full velocity range while minimizing the time overhead and additive noise penalty. The comprehensive study of solutions relying on an arbitrary number of exposures is, however, an important open question which requires careful modeling of the noise characteristics and the per-shot time overhead.

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