

MOTION BLUR IDENTIFICATION BASED ON DIFFERENTLY EXPOSED IMAGES

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ABSTRACT

In this paper we introduce a new method of motion blur identification that relies on the availability of two, differently exposed, image shots of the same scene. The proposed approach exploits the difference in the degradation models of the two images in order to identify the point spread function (PSF) corresponding to the motion blur, that may affect the longer exposed image shot. The algorithm is demonstrated through a series of experiments that reveal its ability to identify the motion blur PSF even in the presence of heavy degradations of the two observed images.

Index Terms— motion blur, image restoration, exposure time, image deconvolution

1. INTRODUCTION

The image degradation, known as motion blur, is caused by the relative motion between the camera and the scene 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, by applying an image restoration approach [1]. 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 [2, 3]. However, 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.

Another category of approaches consists of utilizing either additional hardware or special sensors [4] in order to estimate and correct for the motion of the camera during the exposure time. For instance in [5] the authors proposed the use of an additional camera in order to acquire motion information during the exposure time of the principal camera. The resulted motion information is subsequently used to estimate the motion blur PSF and to recover the blurred image of the main camera. Additional hardware is also used in optical image stabilization solutions that are present in high-end consumer devices. These solutions consists of moving either the image sensor or the optics in the opposite direction of the camera motion such that to maintain a stable image projected on the sensor during exposure.

In this paper we propose a new approach to identify the motion blur by utilizing two image shots acquired at different exposure times. The first shot is captured with a small exposure time in order to avoid motion blur, whereas a second shot is captured using the normal exposure time in the given situation. When a long exposure time is required the second shot may be degraded by arbitrary mo-

tion blur. Our objective is to identify the motion blur PSF in order to recover the original image by restoring the high exposed image shot.

2. THE PROPOSED METHOD

The motion blur identification is carried out in two distinct processing stages. The first stage is meant to provide a initial estimate of the motion blur PSF by analyzing the two input images. Next, this first estimate is further refined in the second stage of the proposed approach that takes into consideration the expected ridge-like appearance of a typical motion blur PSF.

2.1. The initial estimate of the motion blur PSF

We start by formulating a model for the two image shots captured at different exposures. This model takes into consideration that the low exposed image is corrupted by sensor noises, e.g. readout noise, photon shot noise [6], whereas the second shot is mainly affected by motion blur due to camera motion during the exposure time.

Let $g_1(x)$ and $g_2(x)$ denote the low and high exposed image shots. A model for these observations could be expressed by:

$$\begin{aligned} \alpha g_1(\mathbf{x}) &= f(\mathbf{x}) + n_1(\mathbf{x}), \\ g_2(\mathbf{x}) &= d(\mathbf{x}) * f(\mathbf{x}) + n_2(\mathbf{x}) \end{aligned} \quad (1)$$

where the symbol $(*)$ stands the 2D convolution operation, $\mathbf{x} = (x, y)$ denotes the coordinates of a pixel, α accounts for the difference in illumination between the two images, $f(\mathbf{x})$ and $d(x)$ denote respectively the original image and the motion blur PSF. The two additive noise terms $n_1(x)$ and $n_2(x)$ are assumed uncorrelated zero mean Gaussian of variances σ_1^2 and σ_2^2 respectively¹. Given the fact that the low exposed image is more affected by noise than the first image it is also reasonable to assume that $\sigma_2^2 \ll \sigma_1^2$. In addition to the model (1), we impose the energy conservation and positivity constraints on the PSF:

$$\sum_{\mathbf{x} \in \Psi} d(\mathbf{x}) = 1, \text{ and } d(\mathbf{x}) \geq 0, \mathbf{x} \in \Psi, \quad (2)$$

where $\Psi \subset R^2$ denotes the PSF support.

Based on the model (1) we can write

$$g_2(\mathbf{x}) = \alpha d(\mathbf{x}) * g_1(\mathbf{x}) + n(\mathbf{x}), \quad (3)$$

¹The assumption of Gaussian noise is somewhat forced here in order to simplify the theoretical justification. However, the experimental results show that the algorithm is robust to changes in the noise model.

where $n(\mathbf{x}) = n_2(\mathbf{x}) - d(\mathbf{x}) * n_1(\mathbf{x})$ is correlated noise. However, for tractability of the solution, we will consider only the diagonal elements of the covariance matrix of $n(x)$, which are equal to:

$$\sigma^2(d) = \sigma_2^2 + \sigma_1^2 \sum_{\mathbf{x} \in \Psi} d(\mathbf{x})^2 \approx \sigma_1^2 \sum_{\mathbf{x} \in \Psi} d(\mathbf{x})^2, \quad (4)$$

where the last approximation results from the fact that $\sigma_2^2 \ll \sigma_1^2$.

From (3) and (4) we can derive the LMMSE (linear minimum mean square error) estimate of the blur PSF as:

$$D(\omega) = \frac{\alpha G_1^*(\omega) G_2(\omega)}{\alpha^2 |G_1(\omega)|^2 + \sigma_1^2}, \quad (5)$$

where the capital letters stand for the Fourier transforms of the corresponding signals, and the parameter α can be estimated as the ratio between the means of the two images:

$$\alpha = \frac{\sum_{\mathbf{x} \in \Omega} g_2(\mathbf{x})}{\sum_{\mathbf{x} \in \Omega} g_1(\mathbf{x})}. \quad (6)$$

where $\Omega \subset R^2$ denotes the image support.

An initial estimate of the blur PSF is obtained from the inverse Fourier transform of (5). In the following, we present an algorithm for the efficient computation of this initial estimate:

Input: The two images g_1 and g_2 and a rough estimate of the PSF support size, i.e. $S_1 \times S_2$.

Output: The initial estimate of the blur PSF.

1) Register the images g_1 and g_2 , such that to minimize the translational displacement between them, and to cancel other motion parameters (e.g. rotation, scale). In order to obtain a good result the image registration approach used in this step must be robust to image degradations. Such methods have been proposed by several authors [7, 8]. In our implementation we used the method proposed in our previous work [8].

2) Select multiple image blocks of size $W_1 \times W_2$ (i.e. $W_1 > S_1$, and $W_2 > S_2$) from the blurred image (g_2). The selection process is based on the variance of each image block, being preferred blocks that have higher variance, and hence higher likelihood to contain significant transitions or prominent image details. Let us denote by g_2^k , for $k = 1, K$, the K image blocks selected from the image. Similarly, their corresponding blocks in the low exposed image are denoted by g_1^k .

3) Average the K estimates (5) obtained from all pairs of corresponding image blocks g_1^k and g_2^k . In this operation, the Fourier transforms are calculated using Fast Fourier Transform algorithm, and the artifacts due to block boundary are reduced by windowing.

4) Extract the blur PSF estimate by selecting the $S_1 \times S_2$ central part from the $W_1 \times W_2$ inverse Fourier transform of the average calculate in the previous point.

2.2. The identification of the motion blur PSF

In this section we present an algorithm to extract the blur PSF from its initial rough estimate by taking into consideration the prior knowledge about a typical motion blur. The motion blur PSF can be regarded as the projection of the motion trajectory onto the image plane. Consequently, it has the appearance of a ridge that follows a curved trajectory inside the PSF support (e.g. Fig. 1). In each point the amplitude of the ridge is proportional to the translational motion speed of the camera. When the motion is slow, the magnitude of the PSF ridge may exceed the noise present in the initial PSF estimate and hence it can be detected by comparing it against an appropriate

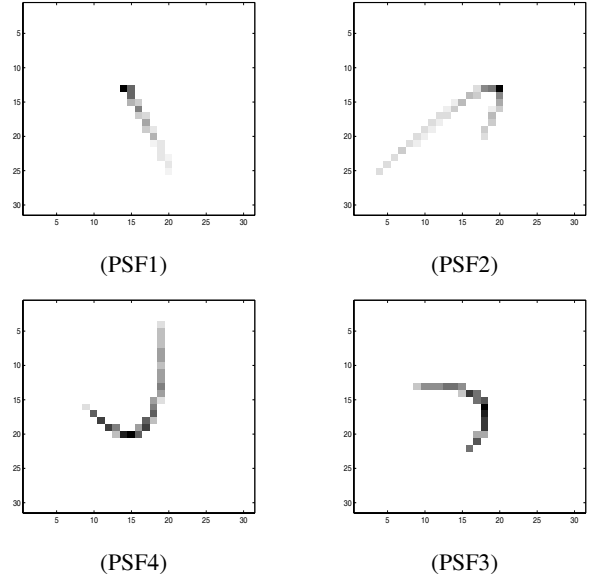


Fig. 1. The motion blur PSFs used in the experiments.

threshold value. However, in regions of high speed motions the amplitude of the PSF ridge may drop below the noise level present in the initial PSF estimate, and hence its detection requires a different strategy than a threshold operation.

Based on these observations we extract the motion blur by adopting a ridge tracking strategy inside the $S_1 \times S_2$ support of the the initial PSF estimate, as described in the following algorithm.

Input: The initial estimate of the blur PSF of size $S_1 \times S_2$, denoted by PSF_0 in the following.

Output: The estimated motion blur PSF.

1) Assuming that the pixels of large values in PSF_0 belong to the real PSF, we start by including those pixels in the PSF. However, in order to avoid including false pixels, it is important to use a high threshold that should be exceeded by the values of the selected pixels, e.g. half of the maximum absolute value found inside the PSF_0 .

2) Estimate the dominant orientation in the neighborhood of each pixel in PSF_0 . For this purpose we employed the least square orientation estimator proposed by Rao in [9]. The orientation is estimated in each pixel based on the gradient vectors in a 3×3 neighborhood centered in the pixel.

3) Mark the pixels which are local maxima along the direction orthogonal to their local dominant orientation. Note that, among these pixels will be also the pixels situated on the PSF ridge that in the end must be included in the final PSF.

4) Fill possible gaps in the PSF ridge line by marking the pixels situated between two neighborhood local maxima along the local dominant orientation.

5) Apply a connected component labeling algorithm in order to identify the connected component regions of the marked pixels inside the PSF_0 support.

6) Construct the final PSF by selecting from PSF_0 the marked pixels that belong to the same connected component to which the maximum value pixel of PSF_0 belongs. Finally the values of the extracted pixels are normalized such that to satisfy the constraints (2).

Blur PSF	SNR (dB) Noisy img.	SNR (dB) Blurred img.	SNR (dB) Restored img.
PSF1	12	14.90	24.87 (0.50)
	8	14.90	24.63 (0.51)
	3	14.90	23.63 (0.67)
	0.1	14.90	19.60 (0.58)
PSF2	12	14.66	26.32 (0.56)
	8	14.66	24.22 (0.61)
	3	14.66	23.50 (0.60)
	0.1	14.66	20.02 (0.57)
PSF3	12	13.70	24.70 (0.70)
	8	13.70	24.00 (0.64)
	3	13.70	20.00 (0.57)
	0.1	13.70	18.70 (0.60)
PSF4	12	13.20	29.20 (0.56)
	8	13.20	27.40 (0.70)
	3	13.20	24.80 (0.57)
	0.1	13.20	20.30 (0.61)

Table 1. Image restoration performance for different noise levels in the low exposed image, and different motion blur PSFs in the high exposed image. The last column shows the average and standard deviation of the restored image SNR in multiple experiments.

3. EXPERIMENTS

In this section we demonstrate the proposed algorithm in a series of motion blur identification experiments. The motion blur PSFs that are used in this simulations are shown in Fig. 1. The PSFs are more realistic than a simple linear motion, including non-uniform power distributions caused by variable motion speed, as well as curved trajectories. In each experiment we create the two input images starting from the original "cameraman" image of size 256×256 on 256 gray level. The image g_1 is obtained by adding white Gaussian noise of different variances plus Poisson noise. The level of noise in each example is then measured by means of the signal-to-noise ratio (SNR). The second image (g_2) is obtained by applying one of the the motion blur PSFs onto the original image. The (SNR) is used also in this case in order to evaluate the degradation of the image in comparison with the original image. In each experiment, the PSF estimated by the algorithm was used to restore the original image by applying the Richardson-Lucy algorithm [1] on to the image g_2 . The ability of the proposed algorithm to estimate the motion blur PSF is thereby evaluated based on the improvement in SNR obtain after deconvolution.

The results obtained in several experiments when using different motion blurs and noise levels are shown in Table 1. For each level of noise and PSF we performed a number of 100 experiments. The average and standard deviation of SNR results obtained in these experiments being included in the last column of the table. We note that the proposed algorithm is able to detect the real PSF quite accurately as long as in all experiments the SNR was improved significantly after restoration. It is also important to remark the fact that the level of noise in g_1 do not degrade significantly the performance of the proposed algorithm. Thus, even for very high levels of noise (e.g. $SNR = 0.1dB$) the algorithm is able to identify the PSF quite accurate in order to determine an improvement of several decibels in the SNR of the restored image.

A visual example of motion blur identification is shown in Fig. 2, where the blur PSF2 was used in conjunction with a noisy image

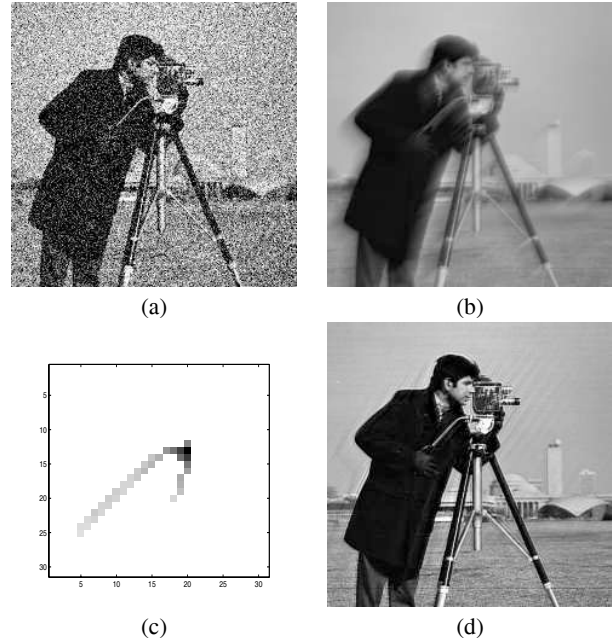


Fig. 2. Example of motion blur identification: (a) the noisy image shot, (b) the blurred image shot, (c) the estimated PSF, and (d) the restored image based on the estimated PSF.

of SNR 3dB. The estimated PSF is quite close to the real one as it reveals also by the visual inspection of the restored image which achieves an SNR of 20dB in comparison to the original image.

The proposed algorithm have been also evaluated on pairs of differently exposed real images. Fig. 4 and Fig. 3 show such examples where the two differently exposed images have been acquired in low-light conditions using different digital cameras. The exposure times for the pairs of acquired images are mentioned in the captions of the two figures. For visibility, the low exposed images shown in these figures have been multiplied with factors larger than one. In each case the restored image has been obtained by applying the Richardson-Lucy algorithm onto the long exposed image shot.

4. CONCLUSIONS

We introduced a new method of motion blur identification based on the availability of two, differently exposed, image shots of the same scene. The proposed method exploits the different degradation models that affect the two images due to their different exposure times. The proposed approach requires relatively low computational power and it is effective in identifying realistic motion blur PSFs, including non-uniform power distributions caused by variable motion speed, as well as curved trajectories. The proposed algorithm has been evaluated through a series of experiments that reveal its ability to detect the motion blur PSF even in the presence of heavy degradations of the two observed image shots. The algorithm was also demonstrated by experiments performed in real conditions using differently exposed image shots acquired with commercial cameras.

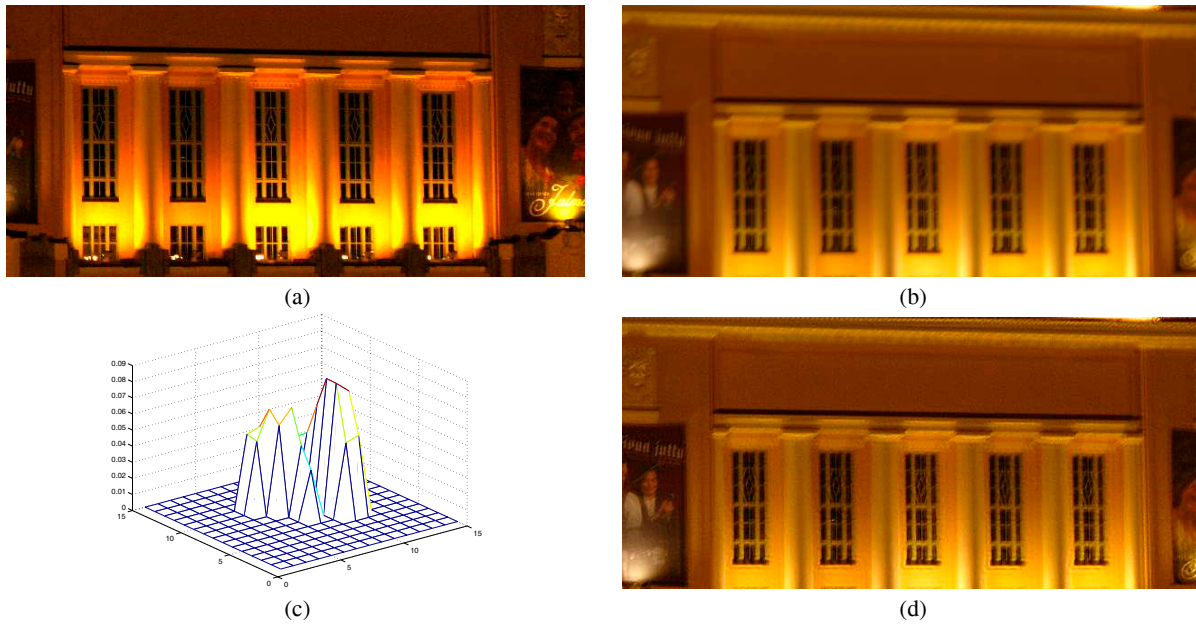


Fig. 3. Example of motion blur identification on real images: (a) the low exposed image shot (1/18 sec), (b) the high exposed image shot (1 sec), (c) the estimated PSF, and (d) the restored image based on the estimated PSF.

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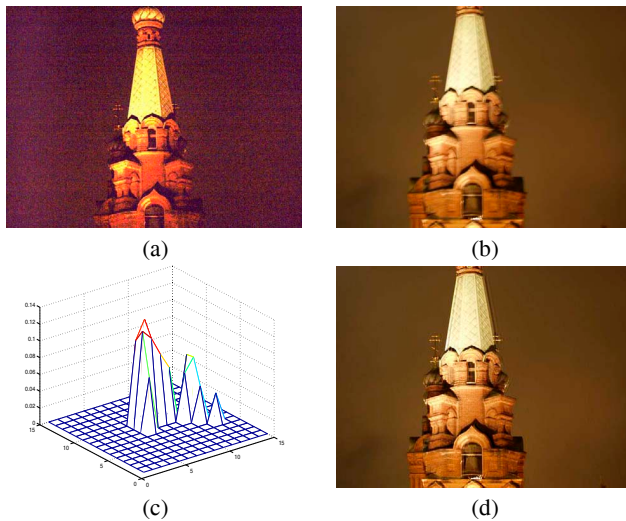


Fig. 4. Example of motion blur identification on real images: (a) the low exposed image shot (1/100 sec), (b) the high exposed image shot (1 sec), (c) the estimated PSF, and (d) the restored image based on the estimated PSF.