Post-Processing Algorithm for Reducing Ringing Artefacts in Deblurred Images

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Abstract. In this paper, we propose grey-scale image post-processing based deblurring framework. Our algorithm is considered to be applied to real camera image, corrupted by linear motion blur. The system outputs a single blur- and ringing-free image obtained as a result of deblurring and deringing steps. Our post-processing scheme based on edge detection approach builds the ringing artifacts' map for each image. This map is used in the deringing routine. Experiment results show that the proposed framework can be used for the efficient removal of motion blur caused by camera shake.

1. Introduction

Motion blur due to camera shake is one of the most common causes of image degradation. Restoration of such images is highly dependent on the estimation of motion blur parameters to define the point spread function (PSF), which describes the response of an imaging system to a moving point source and practically models the blur on the corrupted image. One of the most common degradation function is linear motion blur. The relationship between the observed image $g(x,y)$ and its uncorrupted version $f(x,y)$ is defined by

$$g(x,y) = f(x,y) * h(x,y) \tag{1}$$

where $h(x,y)$ is the PSF convolved with the original image $f(x,y)$. The deconvolution of the blurred image with the PSF that caused the blur allows obtaining the restored blur-free image. The process of deblurring is often called blind deconvolution because it is impossible to find the true PSF.

In our work we, propose image post-processing based deblurring framework, which restores input image by deblurring and de-ringing algorithms. In our case global linear motion model is considered. We estimate motion blur parameters for image and then perform deconvolution. Lucy-Richardson (LR) iterative deconvolution algorithm is employed in the proposed framework.

It is known that the main issues after applying iterative deconvolution algorithms like LR are ringing artifacts that occur close to strong edges making the result perceptually unacceptable. Our framework includes post-processing scheme designed to remove undesirable artifacts. Ringing may be understood as "gaps" in the spatial domain information. We attract temporal domain information contained in the image sequence to recover missing data.

The rest of the paper is organized as follows: in Section 2 brief exploration of previous related work is given; proposed deblurring framework is presented in Section 3; Section 4 contains simulation results; conclusion and discussion are in Section 5.

2. Related Work

Image deblurring approaches can be divided into two groups: blind deconvolution and non-blind deconvolution. [1] provides a broad literature review for the classical problem of single image deblurring. Blind deconvolution approach requires the estimation of initially unknown PSF.

Previous approaches [3] assumed simple parametric forms of PSF shake like, for example, linear or harmonic motion. Later works [2] demonstrate that real motion path of camera shake is more complex and should be described using more sophisticated parametric models.

Fergus et al. [2] used natural image statistics together with sophisticated variational Bayes inference algorithm to estimate PSF of complicated shape. A standard non-blind deconvolution algorithm is employed for image restoration. Proposed in [2] approach provides good results just for the case of small PSF.

Even non-blind deconvolution, where the blurring kernel is known, is an ill-conditioned problem. Blurred images suffer from the lack of high-frequency information and deconstruction through deconvolution brings artifacts such as ringing effect. For example, increasing the number of iterations of Lucy-Richardson algorithm [7] leads to increased amount of ringing in the deblurred image. Our post-processing scheme was designed to reduce ringing artifact appearing after applying iterative deconvolution algorithms.

Spatially invariant PSF estimation was proposed by Bardsley et. al [8]. In other approach by Levin [9] the image is sliced into layers with different PSFs. For each layer motion parameters are constant and PSF is unidirectional. In our work we consider the simple case of linear motion blur, where motion blur parameters can be estimated from the spectrum of blurred image [5].

Deblurring efficiency can obviously be improved from the use of multiple images. Set of images with different blur directions can be used for PSF estimation [10]. Yuan et al. [12] used blurred/noisy image pairs in blurring kernel estimation routine as well as in the process of residual deconvolution that effectively suppresses ringing.

In our approach, input image is deblurred, and result is farther enhanced in order to remove ringing artifacts. The use of one image allows attracting additional information for recovery of data corrupted by ringing.

3. Proposed Post-Processing Based Approach

3.1 Deblurring Framework

As shown in Figure 1, proposed deblurring framework consists of three parts: PSF estimation block; deblurring block implying iterative deconvolution algorithm, such as widely-known Lucy-Richardson algorithm; and finally, the proposed post-processing block designed for ringing artefacts removal. Images with different blur directions can be used as an input.

Figure 1. Proposed Deblurring Framework

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3.2 Motion Parameters Estimation

In order to apply deblurring method such as Lucy-Richardson iterative deconvolution algorithm [7] to blurred images we need knowledge about PSF. There are two parameters to determine: blur length and blur angle. The blur length is a distance, on which each pixel is shifted due to the motion blur. The blur angle is an angle between the vertical line and direction of a motion. Knowing the direction (ϑ) and length (L) of blur, the PSF can be represented by following equation [2]:

$$h(x,y)=\frac{1}{2}\Pi_L(x\cos\theta+y\sin\theta), \qquad (2)$$

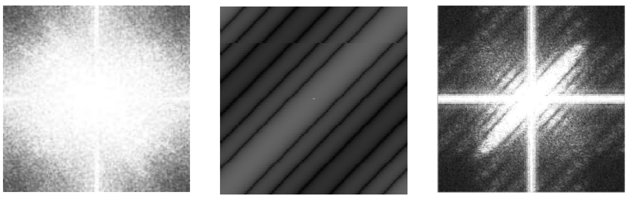
where $\Pi_L(u)$ is a rectangle function defined by

$$\Pi_L(u)=\begin{cases}1 & \left(|u|\le\frac{L}{2}\right)\\ 0 & \left(|u|>\frac{L}{2}\right)\end{cases}, \qquad (3)$$

In our work we considered global motion within the scene, i.e. each pixel in the frame has identical blur characteristics. Also blur is considered to be linear. Processed blur image can be represented by multiplication of un-blurred image and PSF (1), where $f(x,y)$ is the original un-blurred image, $g(x,y)$ is the blurred image, and $h(x,y)$ is a PSF of linear motion blur. The PSF can be estimated using two parameters: blur length and direction. In frequency domain the equation (1) has the form of (4):

$$G(\xi,\eta)=F(\xi,\eta)\otimes H(\xi,\eta), \qquad (4)$$

where (ξ,η) is a spatial frequency, and $G(\xi,\eta)$, $H(\xi,\eta)$, and $F(\xi,\eta)$ are Fourier transforms of $g(x,y)$, $h(x,y)$ and $f(x,y)$ respectively. Since blur corrupted image can be formulated in frequency domain as multiplication of spectrums of PSF and unblurred image, the blurred image spectrum has periodical character (Figure 2).



(a) $G(\xi,\eta)$ (b) $H(\xi,\eta)$ (c) $F(\xi,\eta)$

Figure 2: Fourier spectrum of blurred image (a), linear motion blur PSF (b), and original image (c)

In our algorithm, geometrical approach is used for PFS estimation. The algorithm is as follows. Firstly, we convert input image into frequency domain by performing FFT. The spectrum of a picture has a periodical character due to the motion blur. The distance between the spectrum lines is inversely proportional to the blur distance, the angle between the lines and horizontal axis equals to the blur angle. Therefore, we need only to define these two parameters from the image spectrum. To do this we enhanced by sharpening and binarization the spectrum image to make it clearer, and to reduce estimation error. The next step is to find the angle between horizontal line and spectrum lines. To this end we draw two lines in the image (vertical and parallel), that crosses at chosen start point A (see Figure 3a), and find three nearest intersection points with spectrum lines. Extracting the information from triangles (Figure 3a), we obtain the angle value:

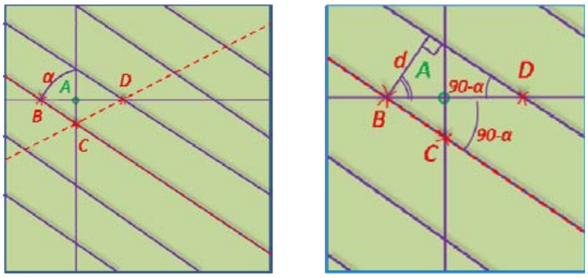
$$tg\alpha=\frac{AB}{AC}, \qquad (5)$$

where AC, BC can be found from triangle in Figure 3a, and α is a desired angle.

Knowing PSF direction we can easy determine the blur distance based on the geometrical information (Figure 3b):

$$d=\frac{BD\times AC}{BC}, \qquad (6)$$

where d is a distance between spectrum lines, and BD, AC, BC can be found from Figure 3b.



(a) angle calculation (b) distance calculation

Figure 3: PSF direction determination

After all we calculate real blur distance using the following equation:

$$D=\frac{N}{d}, \qquad (7)$$

where D is real blur distance and N is an image size.

It was shown that without looses in time consumption we can perform the algorithm four times for different areas in the spectrum picture, and take the average result for distance and angle, that are about 1.7 times more precise. The result of implementation with test images had showed that the error of distance determination is not more than 3 pixels and of angle determination is not more than 2.1 degrees.

3.3 Deblurring

After PSF for input image has been obtained, we can apply one of several deconvolution algorithms proposed in literature [1]. In our framework we imply the Lucy-Richardson iterative deconvolution algorithm [3] for image deblurring. The algorithm maximizes the likelihood that the resulting image, when convolved with the PSF, is an instance of the blurred image. Motion blur parameters obtained at previous step may be used for definition of initial PSF for other iterative blind-deconvolution algorithms. Our post-processing scheme is designed to remove ringing regardless of the algorithm used for deblurring as well as of the number of iterations.

3.4 Proposed Post-Processing Scheme

The results of applying Lucy-Richardson algorithm are often visually inacceptable due to ringing artefacts that tend to occur near strong edges. The amount of ringing depends on the number of iterations: the more iterations were performed at the deblurring stage the more ringing will appear along edges. In our framework, ringing artefacts suppression is carried out at the last stage.

Artefact locations on the deblurred image depend on two factors: edge closeness and the PSF shape. The motion blur parameters (length and angle) define the PSF shape. There should be a way we can predict the artefact location using the information about edges and blur parameters. Experimentally, we have found

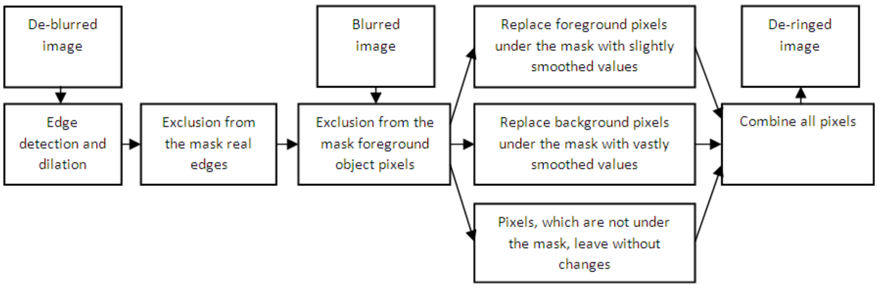


Figure 4: Proposed post-processing scheme

out that the ringing is aligned along both sides of the edges at the distance and angle equal to the length and angle of motion blur. Based on the knowledge about this interrelation, we build the post-processing part of our framework.

Proposed post-processing scheme divides into several steps, as it is shown on Figure 4. In this framework, we use for de-ringing de-blurred with Lucy-Richardson technique image and also initial blurred image. The workflow is as follows.

On the first step, edge detection is performed. Since we need to find only long and important edges and omit weak and short ones, we have to use detector with variable parameters, which provides good detection quality at the same time. Following these restrictions we chose Canny edge detector as one of the most precise, scalable detectors. On the same stage, detected edge mask is dilated, using the information about blur parameters, obtained before using PSF estimation algorithm. Structure element shape is rectangle, which diagonal is PSF vector, multiplied by two. Dilation is necessary to create mask, which would cover ringing artefacts. It was observed, that all the ringing corruptions occurs along strong edges and have periodical decrescent character, and period size is PSF distance. Usually, third order ringing does not make worse picture quality, so we confined our enhancement area to doubled PSF distance size along each detected edge. Thus, we obtain the artefact map for deblurred image, where every pixel significantly corrupted by ringing is marked with “1”, while others are marked with “0”. This map is used in the consequent artefact removal procedure. As an input image on the stage de-blurred image is used.

The second step is exclusion from the mask, acquired on the previous stage. Since the mask after that will be used to smooth picture regions under it, we perform this second step to preserve sharp edges in the output image. The operation here is just subtraction from dilated mask real edges, we obtained with Canny detector.

The next step is to exclude foreground objects from the mask. This is conditioned by the same reason: strong smoothing will corrupt foreground objects, which are in focus, badly. Foreground objects usually have more detailed structure, than background, therefore, we apply to them only slight smoothing. The technique, we employ to discover foreground object is thresholded Laplacian of Gaussian filter. This algorithm is simple, and results are acceptably good. However, any other technique can be used at this point. As an input of the filter we use initial blurred image.

After performing first three operations, practically, we have foreground objects mask and dilated mask. Further, different techniques are employed to different regions in the de-blurred image. Thus, to pixels under the dilated mask, strong smoothing filter is applied, slight smoothing – to foreground object pixels, and other regions are copied from de-blurred image.

The last step is junction of all the pixels, modified on previous stage.

As a result, on the output of the scheme we have image, which is a combination of de-blurred image itself and smoothed with different coefficients regions of the same de-blurred image.

4. Results

We apply our algorithm to a number of real images with varying degree of blur. Firstly, blur parameters estimation is employed. As a result of the estimation stage, we have two parameters: direction and distance of camera or object moving (remind that we consider general motion and PSF character is linear). The second operation is applying Lucy-Richardson algorithm. There is no modifications were made to the de-blurring scheme. Finally, proposed ringing artefact removing algorithm was employed to de-blurred image.

On Figure 5 some of the results are shown. On the top line blurred images, taken with real camera are presented, the second line is the results of Lucy-Richardson de-blurring stage, and the bottom are improved with de-ringing scheme results. As it can be observed, significant ringing effect occurs along strong edges, such as man’s silhouette, mast, propeller or camera lace. The majority of these artefacts removed using proposed scheme, as it shown on the Figure 5 (bottom line).

5. Conclusion

In the paper, real camera image, corrupted by linear blur, enhancement algorithm is proposed. The whole scheme is divided into three main parts: PSF parameters estimation, de-blurring, and de-ringing. For blur parameter evaluation geometrical method is used, which provides quite accurate estimation of both parameters. These data are further used in Lucy-Richardson de-blurring scheme, which output image is corrupted by ringing artifacts. The third part is intended to remove these artifacts to obtain acceptable quality output image. Applying this scheme to different real images, we obtain results, de-blurred, artifact-free pictures. The main merit of the proposed algorithm is the use only one blurry image as an input. Many recent works in the area employ several corrupted images of the same scene to combine information and obtain blur-free image. Also our method does not demand any preliminary knowledge about blur parameters, all the data, obtained from available input photograph.

Although notable image enhancement can be observed from the results, obtained with the scheme, not all the artifacts can be removed from initial blurry image (see fine details, like chimney, on Figure 5). The room for improvement here is to get use more accurate foreground objects detection algorithm, but it will complicate the algorithm, that leads to time and memory consumption. Another lack is the assumption of linearly blurred input image, even though we do not need very precise information about blur parameters, and wide curve shaped PSF can be handled as line, only a few real pictures are suited to linearity condition.

Figure5: The results of the ringing artefact removing algorithm. *First row:* The blurred images with varying blur direction and estimated PSF distance from 10 to 15 pixels. *Second row:* The results produced by deblurring algorithm. *Bottom row:* The results produced by deringing algorithm

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