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DEBLURRING OF PHOTOGRAPHIC IMAGES

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Abstract. The degradation of photographic images is mostly caused by geometric distortion or a blur. Blur is usually caused by a movement of a camera during the image capture or by the movement of a photographed subject when long exposure time is used. Additional noise can be added by a camera sensor. The restoration process means to achieve "the best" approximation of the original image. We compared two mathematical models of restoration: the Wiener filter deconvolution and the Lucy-Richardson algorithm. The two approaches and the results are discussed in this paper.

Key words. Image restoration, Blur, Wiener filtering, Lucy-Richardson algorithm

1 Degradation Model

The degradation of a photographic image can be caused by many factors such as a geometric distortion or a blur. The geometric distortion is often caused by using of a wide-angle lens. The blur is caused by a movement of a camera during the image capture or by the movement of a photographed subject when long exposure time is used. Other type of blur can be caused if the subject is out-of-focus.

A blurred or degraded image can be approximately described by the expression [2]

$$g = h * f + n \tag{1}$$

where: g is the blurred image, h is the distortion operator, f is the original image, and n is an additive noise. h is also called PSF - the point-spread function. PSF describes the distortion (the blur in our case). PSF function, when convolved with the original image f, creates the distortion The "*" stands for convolution; f represents an "ideal" original image.

2 Reconstruction Methods

The deblurring means to deconvolve the blurred image with the appropriate PSF. The quality of the deblurred image is mainly determined by knowledge of the PSF. The reversing process of the effect of convolution is called deconvolution. The deconvolution is often done in frequency domain, where the process becomes a simple matrix multiplication. In the frequency domain the PSF is represented by the optical transfer function (OTF) [1, 3]. The OTF is the Fourier transform of the PSF and it describes the response of a linear, position invariant system to an impulse.

When the photograph is blurred the parameters of the original PSF may be partly known or may not be known at all. During the deblurring process many iterations with varying parameters may be needed to achieve an image that is “the best” approximation of the original image. Here we compared two types of de-convolution functions: the Wiener filter deconvolution [1] and the Lucy-Richardson deconvolution [3].

2.1 Wiener Filter Deconvolution

The primary assumption is that the blurred image *g* was created by convolving the original image with a point-spread function. Some noise can be added too. The Wiener filter deconvolution [1, 2] finds the optimal deblurred image in the sense of the least mean square error between the estimated and the original images

$$e^2 = E\{(f - \hat{f})^2\}, \tag{2}$$

where *E* denotes the mean value. The solution of finding the estimate $\hat{f}$ is done in frequency domain:

$$\hat{F}(u,v) = \frac{|H(u,v)|^2}{H(u,v)|H(u,v)|^2 + |N(u,v)|^2 / |F(u,v)|^2} G(u,v) \tag{3}$$

The uppercase letters indicate that the computation is done in the frequency domain. $H(u,v)$ is the degradation function, $|G(u,v)|$ is the Fourier transform of the degraded image, $|N(u,v)|^2$ is the power spectrum of noise, $|F(u,v)|^2$ is the power spectrum of the undegraded image *f*. Without the presence of noise the Wiener filter reduces to the inverse filter.

2.2 Lucy-Richardson Deconvolution

Non-linear optimization iterative techniques have been accepted only recently because of increase of inexpensive computing power. The Lucy-Richardson algorithm uses iterative optimization. Information about the additive noise is not necessary. The Lucy-Richardson algorithm uses maximum likelihood approach assuming Poisson noise statistics [3]. Maximizing the likelihood function gives the equation that is satisfied when the following iteration converges:

$$\hat{f}_{k+1}(x,y) = \hat{f}_k(x,y)\left[h(-x,-y) * \frac{g(x,y)}{h(x,y) * \hat{f}_k(x,y)}\right]. \tag{4}$$

The “*” indicates convolution, $\hat{f}_k(x,y)$ is the estimate of the image during the iteration *k*, other symbols have the obvious meaning defined above.

3 Experiments and Results

The experiments were done with different sizes of the blur. The following results show how different method affects the deblurring. The images are of the size 256 x 256 pixels.
We experimented with the Wiener deconvolution method and the Lucy and Richardson non-linear iterative method. The PSF was generated to simulate motion. The angle of the motion was 0 and 45 degrees respectively. The length of the motion was set to 4, 8, 12, 16, 20 and 24 pixels.

The question when to stop the Lucy Richardson algorithm is in general difficult to answer as it is with many non-linear methods [3, 4, 5, 6]. We performed the Lucy-Richardson deconvolution tests with different number of iterations: 5, 10, 20, 50, 100, and 500. Then we computed the mean square error between the result and the original non-degraded image. The results – how the number of iterations influences the Lucy-Richardson iterative method were compared to the results acquired by the Wiener deconvolution method – both, quantitatively and visually. The summary of the results – the mean square error for different methods is in Table 1.

PSF		WIENER	LUCY – RICHARDSON					
THETA	LENGTH		Num.iter. 5	Num.iter. 10	Num.iter. 20	Num.iter. 50	Num.iter. 100	Num.iter. 500
0	4	0.01745	0.02530	0.02087	0.01532	0.01443	0.01746	0.04267
0	8	0.02554	0.04505	0.03414	0.02563	0.02068	0.02375	0.05464
0	12	0.02735	0.05866	0.04514	0.03539	0.02907	0.02897	0.06490
0	16	0.03373	0.06995	0.05622	0.04521	0.03462	0.03430	0.07785
0	20	0.03242	0.07969	0.06629	0.05675	0.04215	0.03744	0.07997
0	24	0.03197	0.09066	0.07508	0.06188	0.04487	0.03629	0.08228
45	4	0.01209	0.02002	0.01485	0.01176	0.01070	0.01208	0.01970
45	8	0.02272	0.04056	0.03214	0.02416	0.01985	0.02281	0.04099
45	12	0.02593	0.05150	0.03882	0.02915	0.02374	0.02624	0.04314
45	16	0.02871	0.06182	0.04820	0.03734	0.02916	0.02944	0.04477
45	20	0.03545	0.07016	0.05599	0.04418	0.03540	0.03637	0.08290
45	24	0.03794	0.07596	0.06149	0.04906	0.03928	0.04046	0.05502

Table 1. Summary of the mean square errors

The original image is in Figure 1. The examples of the blurred images with the direction of motion at the angle of 45 degrees and the length of the blur of 8 and 24 pixels are in Figure 2a, b. The result of the restoration using Wiener deconvolution and PSF with parameters representing the movement at the angle of 45 degrees 8 or 24 pixels shift are in Figures 2c, and 2e. The results of the restoration using Lucy-Richardson algorithm with the same parameters as above and 50 iterations are in Figures 2d, and 2f. Notice that the mean square error was minimal at 50 iterations and close to the error achieved with the Wiener method, see Table 1.

Other experiments were done with the number of iterations of the Lucy-Richardson algorithm. Some of the results are summarized in Table 1. The example of the blurred image with the PSF simulating motion at the angle of 45 degrees and the shift of 16 pixels is in Figure 3a. The results of the restoration using Lucy-Richardson algorithm using the same parameters as above after 5, 50, 500 iterations are in Figure 3b, c, and d. The application of the Lucy-Richardson algorithm may give smoother images with less ringing effect more acceptable for “visual purposes” although the mean square error is greater, see Table 1. Compare the result of the Lucy Richardson algorithm after 500 iterations with the Wiener restoration in Figures 3d, e. The Lucy-Richardson algorithm is much slower then the Wiener restoration because of its iterative nature.

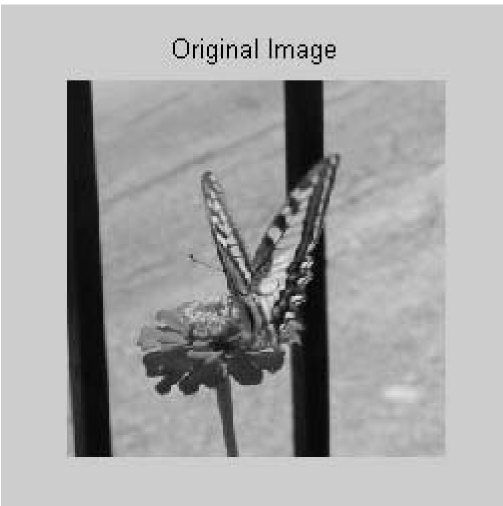

Figure 1 The original image

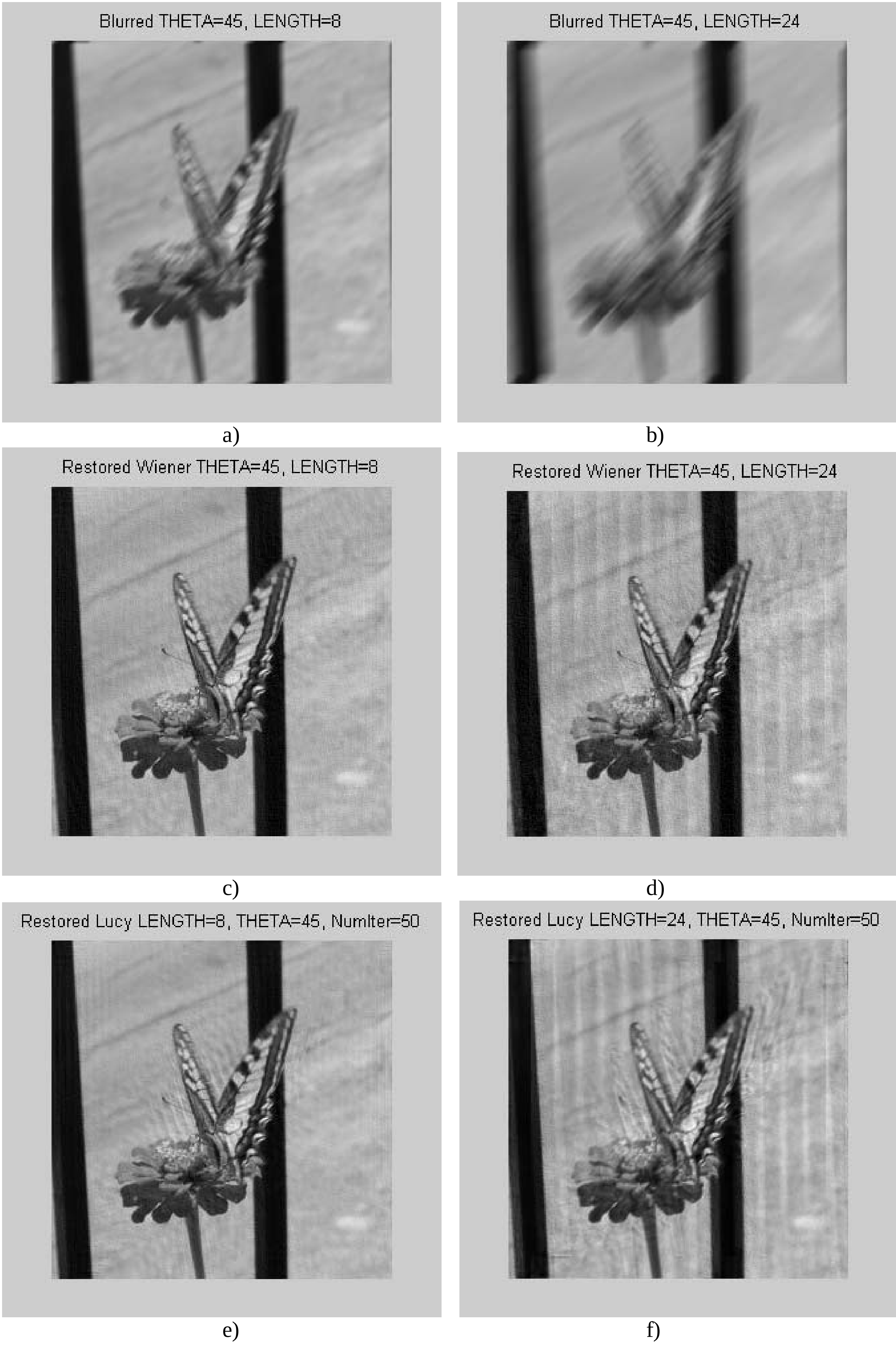

Figure 2 Blurred and restored images. a, c, e - the length of 8 pixels and angle of 45 degrees, b, d, f - the length of 24 pixels and angle of 45 degrees.

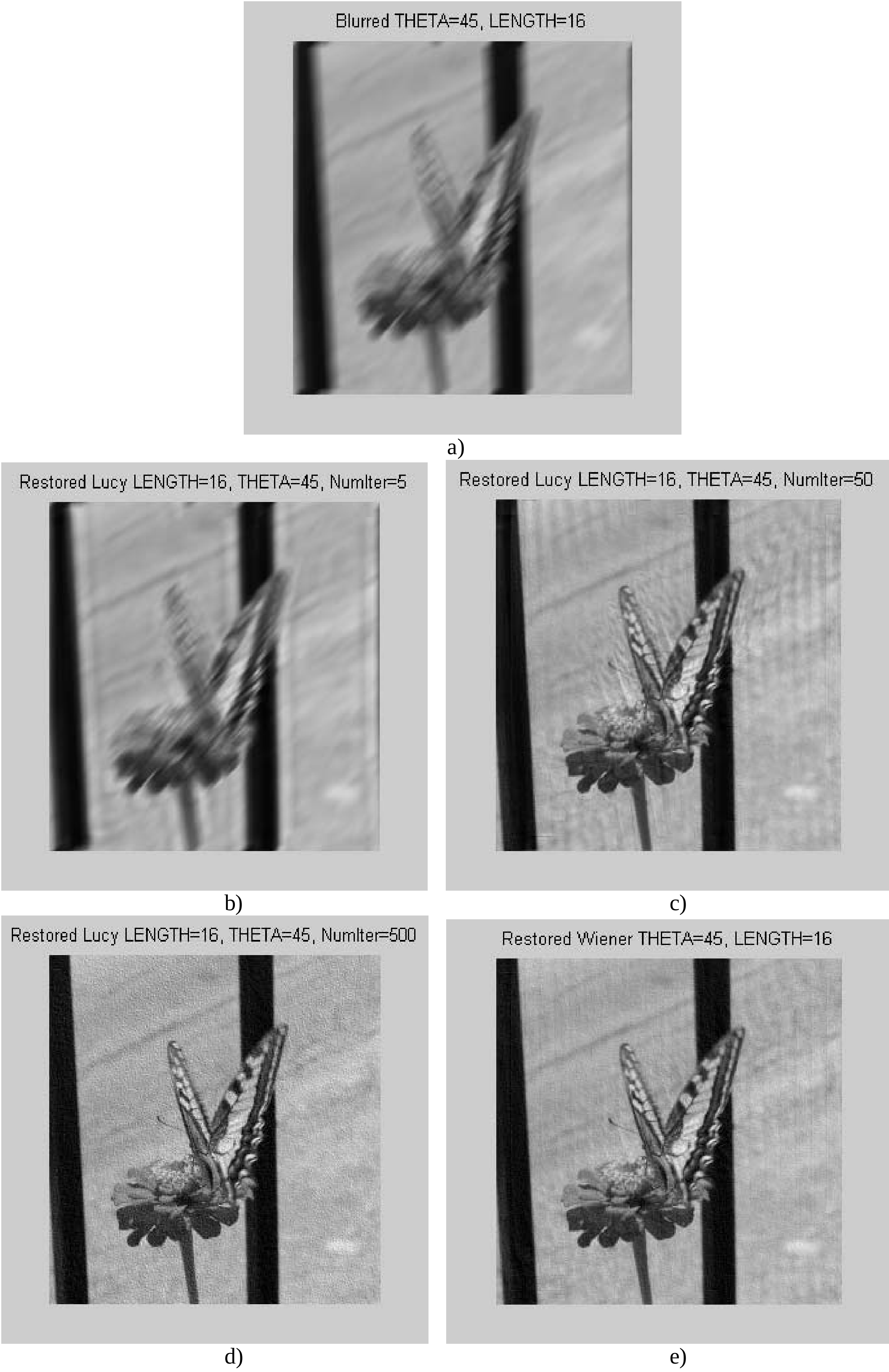

Figure 3 Lucy – Richardson deconvolution for different number of iterations b) 5, c) 50, d) 500. Compare the results c) and d) with Wiener restoration e).

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