Faster Deblurring for Digital Images using an Ameliorated Richardson–Lucy Algorithm

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Abstract: Blur is one popular artifact that degrades digital images due to various unavoidable real-life limitations. Image deblurring is the recovery of an acceptable-quality image from a blurry image. This topic has been a major research focus because of the noticeable upsurge in the use of digital images and imaging systems in many real-world applications. Many intricate and simple algorithms exist for image deblurring. Accordingly, the Richardson–Lucy (RL) algorithm is highly renowned in the field of image deblurring. However, it requires numerous iterations in many situations to produce results with sharp attributes. Hence, an ameliorated RL algorithm is proposed in this article to accelerate the deblurring process by reducing the number of required iterations. The key novelties of the proposed algorithm lie in the addition of a specially designed acceleration factor and in raising part of the algorithm to the power of two. These modifications are achieved experimentally, in which they significantly reduced the number of required iterations to obtain the desired results. Intensive experiments on naturally and synthetically-blurred images reveal that the proposed algorithm performs better than the original and accelerated counterparts in terms of recorded accuracy, perceived quality, and processing speed.

Keywords: Ameliorated Richardson–Lucy algorithm, Artifacts, Deconvolution, Image deblurring, Fewer Iterations

1. Introduction

In digital image processing, image deblurring is the recovery of an acceptable-quality image from a blurred image, and has been a defying open research field for many years [1]. Despite substantial improvements in photographic technologies, the blur artifact is considered a major causal factor of poor image quality [2]. In addition, it can affect digital images due to various unavoidable real-life limitations [3]. Thus, image deblurring is an ill-posed problem that is deemed a vital pre-processing step in various image processing applications [4]. In many deblurring studies, blur is modeled by a convolution process, as follows [5]:

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

where g is the observed blurry image, f is an ideal (true) image, $\otimes$ is a convolution operator, h is a point spread function (PSF), which is also called the blurring kernel, and n is additive noise. Accordingly, estimating image f from observed image g is termed image deblurring. If the PSF is known a priori, then the process is called non-blind deblurring. However, if the PSF is unknown, the process is called blind deblurring [6]. In recent years, noteworthy progress has been achieved in the field of image deblurring [7]. In view of this, extensive research has been conducted regarding non-blind deblurring methods. Thus, a compendious review regarding such methods is given in Section 2.

It is well known that many non-blind deblurring methods exist and have been utilized in various imaging applications to support a variety of solutions. One method of interest is the Richardson–Lucy (RL) algorithm, which was developed based on Bayes's theorem [8] and has been used extensively in many scientific fields [9] to recover a latent image from a blurry one [10]. The RL algorithm is an attractive method for producing sharp attributes in processed images. As is known, gradients and edges carry essential visual information in digital images. Therefore, most techniques in image processing need sharp edge information to yield acceptable quality results [4].

Various available non-blind deblurring methods, such as those listed in Section 2, have many advantages and a few disadvantages. The advantages encourage specialists to use such methods for solving many real-world deblurring problems, while the disadvantages encourage researchers to improve the methods. Therefore, the RL algorithm has been rich research material since its inception. Accordingly, the RL algorithm has many advantages, including a low-complexity structure, easy implementation, provision of acceptable results in many situations, and tolerance for minor PSF estimation errors. Moreover, it does not need any information from the ideal image.

Despite that, the algorithm has a few disadvantages, including its tendency to amplify latent image noise [11], and to produce unwanted boundary [12] and ringing artifacts when further iterations are involved [6]. In addition, this algorithm needs numerous iterations to produce satisfactory results [13]. How to provide a good deblurring method is an active field of research in digital image processing. Hence, an ameliorated RL algorithm is proposed in this article to accelerate the deblurring procedure by reducing the number of required iterations. The dataset for this study involves different naturally and synthetically-blurred images to be used for experimental and comparison purposes. Additionally, the dataset was collected from publicly available databases on the web.

Regarding comparable methods, the proposed algorithm is compared to the original RL and the improved RL algorithms in [14]. Regarding image quality assessment (IQA) metrics, many of them exist for numerical benchmarking of an image's perceived quality. Various IQA metrics were studied, and two were selected: the local phase coherence-based sharpness index (LPC-SI) [15] and the sparse representation–based image sharpness index (SPARISH) [16]. Further information concerning the dataset and the used IQA metrics is provided in Section 4. The rest of this article is organized as follows. In Section 2, a compendious review regarding the available non-blind deblurring methods is given. In Section 3, the proposed algorithm is explained in detail. In Section 4, the required experiments, comparisons, discussions, and related information are presented. Finally, a concise conclusion is given in Section 5.

2. Related Works

In this section, various non-blind methods for image deblurring are reviewed. It is known that image deblurring is considered a classic problem with carefully researched methods of various concepts. Low-intricacy methods, including expectation maximization deconvolution [17], gold deconvolution [18], the regularized filter [19], the Metz filter [20], the Wiener filter [21], Van-Cittert deconvolution [22], Richardson–Lucy deconvolution [14], Hunt's Poisson MAP deconvolution [23], Landweber deconvolution [24], least-squares deconvolution [25], the inverse filter [26], the Tikhonov filter [27], the truncated singular value decomposition filter [28], and Gaussian priors deconvolution [29], have been utilized in various image-related applications for many reasons, such as low-cost implementation, ease of use, and rapidity.

Furthermore, such methods are preferred for use in imaging systems with low hardware specs. However, they have drawbacks, because they introduce several undesirable degradations to the processed image. As a consequence, various innovative ideas and new concepts have been introduced to provide better deblurring procedures. Accordingly, different new directions were proposed in recent years, which comprise approaches that utilize hybrid systems [30], sparsity information [29], image statistics [31], multi-image information [32], and other new models. However, such models increase the complexity of deblurring procedures while providing better-quality results. All deblurring methods share the same goal of recovering a good-quality image from a blurry one. However, the vast majority of such methods achieve this goal by utilizing high-complexity calculations. Such a feature is a drawback for systems with limited resources. Hence, it is favorable to develop a low-complexity deblurring method that needs few calculations and attains acceptable results.

3. Ameliorated RL Algorithm

As mentioned earlier, the RL algorithm is addressed in this study due to its high-profile in the field of digital image processing. In addition, it is an iterative non-blind algorithm that has many pros and few cons [33]. The original RL algorithm is in Eq. (2) [14]:

$$\hat{f}_{k+1} = \hat{f}_k \left(h * \frac{g}{h \otimes \hat{f}_k} \right) \tag{2}$$

where k is the iteration number; $\hat{f}_k$ is the estimate of f after k iterations; $\hat{f}_{k+1}$ is the estimated image at the next iteration; * is a correlation operator. To start the algorithm, an initial estimate is required for $\hat{f}_k$. Thus, $\hat{f}_k = g$ in the first iteration. A simple acceleration method was proposed by Meinel [34], in which the RL algorithm was altered by introducing exponential correction factor n, as seen in Eq. (3):

$$\hat{f}_{k+1} = \hat{f}_k \left(h * \frac{g}{h \otimes \hat{f}_k} \right)^n \tag{3}$$

where $n > 1$. This addition is beneficial in retaining non-negativity though later stages of the iteration process. By doing so, the algorithm converges faster, and fewer iterations are used to achieve the desired results. When performing many experiments for the purpose of finding the best value for n, it turns out that the algorithm performs best when n=2. Therefore, as an alternative to n, the value 2 is used in the proposed algorithm. In addition, a specially designed acceleration factor, λ, is added to speed up the deblurring process by allowing less iteration use. Accordingly, the proposed algorithm is in Eq. (4):

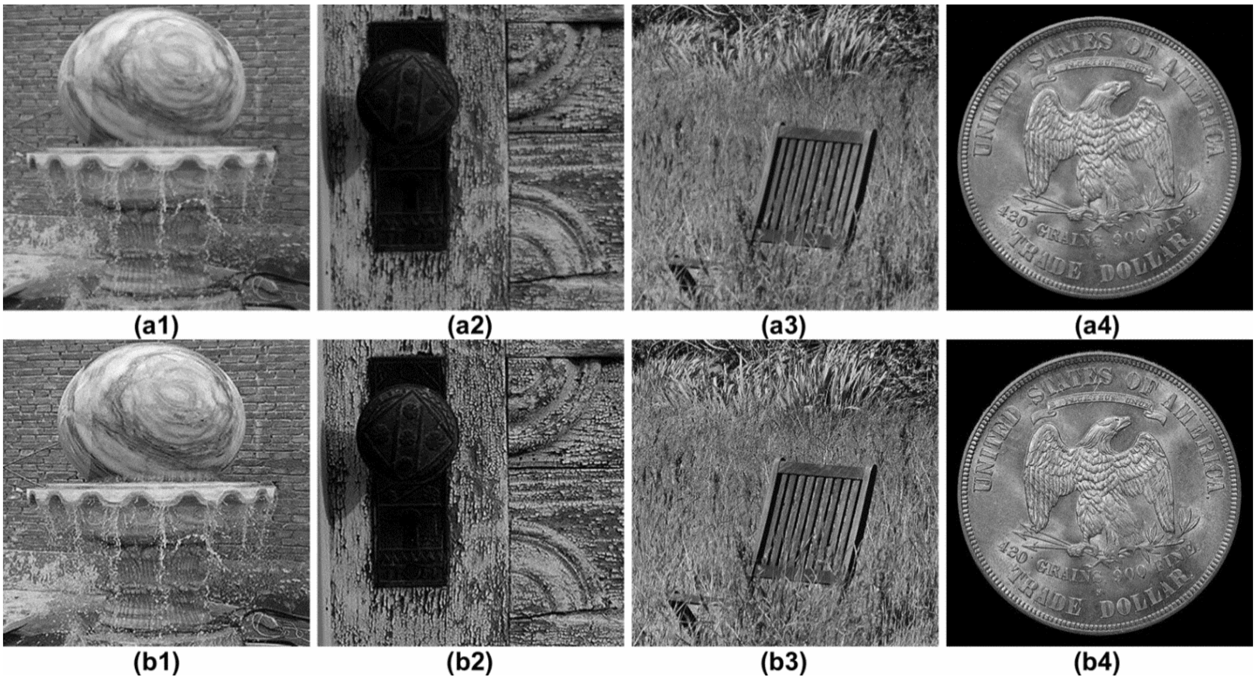

Fig. 1. Results from recovering naturally-degraded images (a1)-(a4) are naturally-blurred images, (b1)-(b4) are images deblurred by the proposed algorithm with 5, 7, 9, and 10 iterations, respectively.

$$\hat{f}_{k+1} = \hat{f}_k \left(h * \frac{\lambda}{h \otimes \hat{f}_k} \right)^2 \tag{4}$$

$$\lambda = \left(g - \left(\eta \otimes g \right) \right) \tag{5}$$

$$\eta = \begin{bmatrix} 0 & 0.25 & 0 \\ 0.25 & -1 & 0.25 \\ 0 & 0.25 & 0 \end{bmatrix} \tag{6}$$

where η is a special kernel that has a significant effect in accelerating the deblurring process. Acceleration factor λ represents a slightly sharpened version of the degraded image *g*, wherein that slight sharpness is mainly attained by utilizing η. When using λ in Eq. (4), it significantly helped the algorithm to converge faster towards the recovery of acceptable results. The factor λ is computed one time only—before starting the iteration process. Then, it is used in every iteration to assist in determining a better estimation for image *f*. The proposed algorithm was developed experimentally and is expected to be used in many scientific fields.

4. Results and Discussion

In this section, the required preparations, computer experiments, comparisons, discussions, and other important information are addressed. Computer experiments and comparisons were carried out to demonstrate the abilities of the proposed algorithm against its original and accelerated counterparts with a dataset of various naturally and synthetically-blurred images. Accordingly, the synthetically-blurred images were used for comparison purposes to test the proposed algorithm under diverse conditions in an attempt to better comprehend its behavior and performance. Moreover, naturally-blurred images were used for experimental purposes to show the true processing abilities of the proposed algorithm with blurred images that are produced by real-world imaging systems [35].

The code of the proposed algorithm was written with Matlab 2017a, and all experiments were conducted on a computer with a 2.6 GHz Intel Core I5-3320M processor and 8 GB of memory. Additionally, the quality of the comparison results was measured by two advanced no-reference IQA metrics: LPC-SI and SPARISH. These metrics can provide supplementary information regarding the sharpness of the assessed images. Basically, the output of these metrics is greater than zero, where a higher value indicates that the evaluated image has less blur and sharper attributes. For the synthetically-blurred images, two types of blurring kernels (motion and Gaussian) were utilized and generated using the "*fspecial*" function in Matlab similar to [36, 37]. The associated parameters of the "*fspecial*" function are *motion* and *gaussian*. Other settings regarding the used blurring kernels can be found in Table 1.

The results of processing naturally-blurred images are displayed in Figs. 1 and 2, while the results of the achieved comparison are demonstrated in Fig. 3. Table 1 exhibits the recorded accuracies of the used IQA metrics. In view of the results from processing the naturally-blurred images listed in Figs. 1 and 2, it can be seen that the proposed algorithm provided visually pleasing results for many types of images, even with a low number of iterations. In addition, no major visible flaws are noticed in the results. Hence, it is practical to say that the proposed algorithm can rapidly yield satisfactory results with sharp edges, preserved information, and highlighted features.

In view of the results from processing the synthetically-

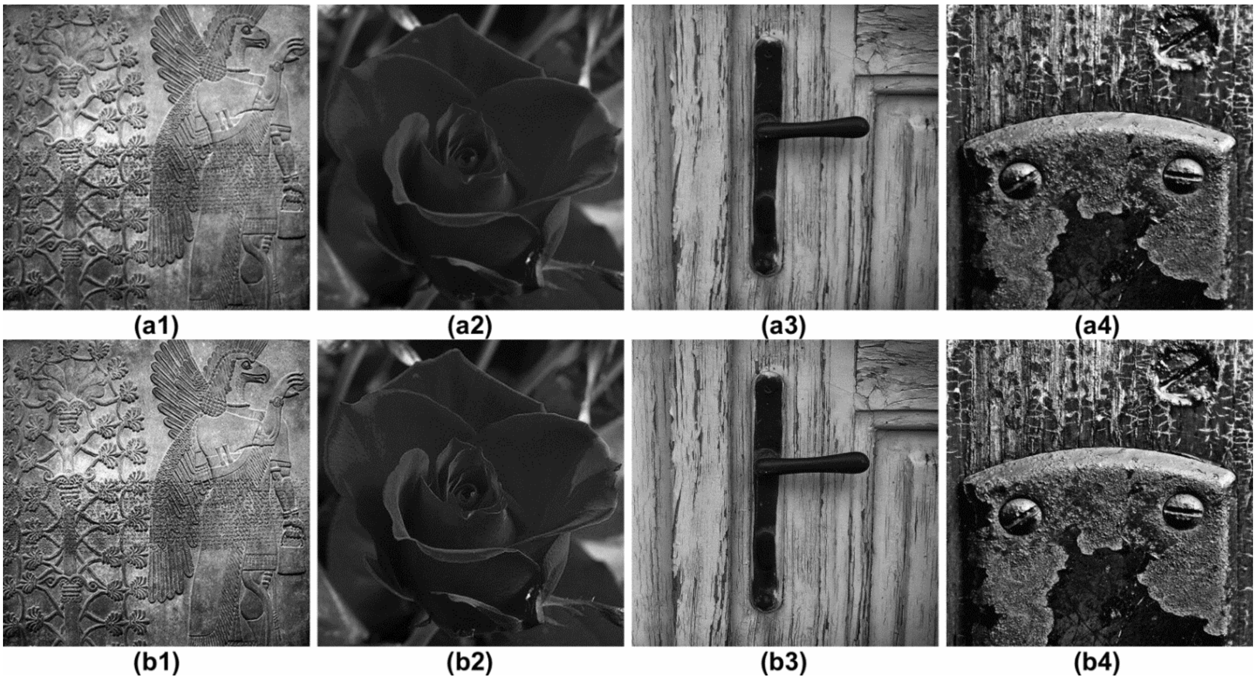

Fig. 2. Results from recovering naturally-degraded images (a1)-(a4) are naturally-blurred images, (b1)-(b4) are images deblurred by the proposed algorithm with 10, 15, 20, and 25 iterations, respectively.

Table 1. LPC-SI and SPARISH values for the proposed and the comparable algorithms.

Methods	Blur	Variables	ITR	LPC-SI	SPARISH	Time
Degraded	Motion	L=10, T=10	N/A	0.9591	9.5177	N/A
	Motion	L=20, T=15	N/A	0.9676	5.7964	N/A
	Gaussian	s=9×9, σ=1.5	N/A	0.9422	5.4328	N/A
	Gaussian	s=11×11, σ=2.5	N/A	0.8948	2.7846	N/A
Original RL algorithm	Motion	L=10, T=10	100	0.9720	13.5273	2.1524
	Motion	L=20, T=15	140	0.9771	11.2126	4.4657
	Gaussian	s=9×9, σ=1.5	90	0.9760	11.8301	2.3039
	Gaussian	s=11×11, σ=2.5	150	0.9743	6.9362	4.5506
Meinel's RL algorithm	Motion	L=10, T=10	50	0.9720	13.5361	1.1154
	Motion	L=20, T=15	70	0.9772	11.1990	2.3035
	Gaussian	s=9×9, σ=1.5	45	0.9760	11.8593	1.1848
	Gaussian	s=11×11, σ=2.5	75	0.9744	6.9456	2.3893
Proposed algorithm	Motion	L=10, T=10	20	**0.9758**	**15.2414**	**0.2652**
	Motion	L=20, T=15	40	**0.9801**	**13.0015**	**0.6273**
	Gaussian	s=9×9, σ=1.5	20	**0.9772**	**12.7654**	**0.3083**
	Gaussian	s=11×11, σ=2.5	40	**0.9759**	**7.0446**	**0.6417**

ITR =iterations, S = size, L = length, T = theta

blurred images listed in Fig. 3 and Table 1, it can be seen that proposed algorithm performed the best in terms of recorded accuracy, perceived quality, and processing speed. In addition, the obtained results have no visible boundary artifacts, no visible ringing artifacts, suppressed noise, and acceptable edge information. In addition, the proposed algorithm achieved proper acceleration for the deblurring process, with high-quality results attained with the number of iterations significantly lower than the original and Meinel's RL algorithms. This is significant because such results can be achieved with a simple modification. Regarding Meinel's RL algorithm, it was noticeably faster than the original RL algorithm, yet strikingly slower than the proposed algorithm, with IQA readings that are near those of the proposed algorithm. However, the utilized number of iterations is significantly higher than the number needed for the proposed algorithm. Providing unorthodox improvements for the RL algorithm is challenging, since many research works regarding such a topic were proposed, and the chance of delivering different

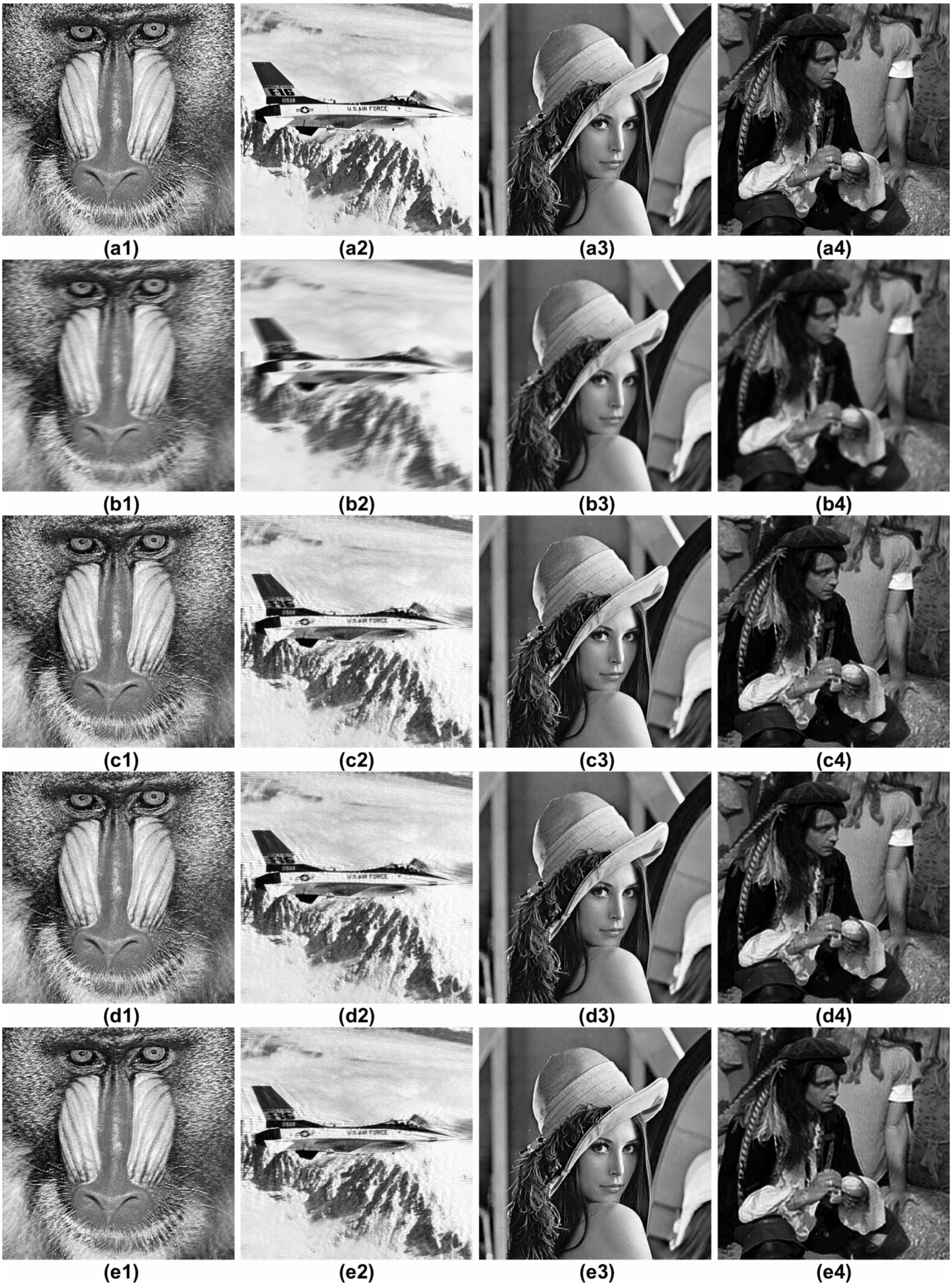

Fig. 3. Results of recovering synthetically-blurred images (a1)-(a4) ideal grayscale images, (b1)-(b4) are synthetic-degraded images by motion blur (L=10, T=10), motion blur (L=20, T=15), Gaussian blur (s=9×9, σ=1.5) and Gaussian blur (s=11×11, σ=2.5), respectively; The rest of the images were deblurred by (c1)-(c4) the original RL algorithm with 100, 140, 90, and 150 iterations, (d1)-(d4) Meinel's RL algorithm with 50, 70, 45, and 75 iterations, (e1)-(e4) the proposed RL algorithm with 20, 40, 20, and 40 iterations.

improvements is somewhat slight. However, innovative improvements have been proposed and successfully implemented in this study. To the best of the author's knowledge, an RL algorithm with the introduced modifications is still missing from the literature.

5. Conclusion

In this article, an ameliorated RL algorithm is introduced to deblur images using fewer iterations than the original and accelerated counterparts. Accordingly, two modifications (adding a specially designed acceleration factor and raising part of the algorithm to the power of two) were successfully achieved to accelerate the deblurring procedure. To demonstrate the performance of the proposed algorithm, it was tested with different naturally and synthetically-blurred images collected from various free image databases. In addition, it was evaluated through intensive computer experiments with two of the algorithm's counterparts and two complex IQA metrics. The obtained results revealed that the proposed algorithm outperforms the comparable algorithms in terms of processing speed, visual perception, and recorded accuracy. At the same time, the proposed algorithm appears to be much faster than the compared algorithms, since sharper results are acquired with significantly fewer iterations. Finally, it is expected that the proposed algorithm can be used with various real-world image processing applications.

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