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Blind and Non-Blind Deconvolution-Based Image Deblurring Techniques for Blurred and Noisy Image

Shayma Wail Nourildean iD *

Communication Engineering Department, University of Technology, Baghdad, Iraq.

Corresponding author:

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Shayma Wail Nourildean

Communication Engineering Department, University of Technology, Baghdad, Iraq.

Abstract: Image deblurring is a common issue in low-level computer vision aiming to restore a clear image from a blurred input image. Deep learning innovations have significantly advanced the solution to this issue, and numerous deblurring networks have been presented to recover high-quality images. This study aims to investigate the impact of Blind deconvolution and Non-Blind Deconvolution (Weiner Filter, Regularized Filter, and lucky Richardson) deblurring techniques and blind deconvolution to retrieve the original image from the blurring and the noisy images. Point Spread Function (PSF) is required to perform the deconvolution process. MATLAB program is utilized in this study as a suitable tool for image processing. Peak to Signal Ratio (PSNR) and structural index similarity (SSIM) are the major parameters used to examine image quality. The results showed that the Regularized Filter was an effective technique to deblur the blurry image, and it achieved the largest PSNR and best SSIM with the prior information about the PSF for different degrees of blurring angle. These four deblurring techniques were unsuccessful in restoring the original image from the image with Gaussian noise.

تقنيات إزالة الصورة الضبابية والصاخبة

شيماء وائل نور الدين

قسم هندسة الاتصالات / الجامعة التكنولوجية / بغداد – العراق.

الخلاصة

يعد تشوه الصورة مشكلة شائعة في رؤية الكمبيوتر منخفضة المستوى والتي تهدف إلى استعادة صورة واضحة من صورة إدخال ضبابية. لقد طورت ابتكارات التعلم العميق الحل لهذه المشكلة بشكل كبير، وتم تقديم العديد من شبكات التدمير من أجل استعادة الصور عالية الجودة. الهدف من هذه الدراسة هو التحقيق في تأثير تقنيات إزالة التداخلات العمياء والتفكك غير الأعمى (مرشح وينر، مرشح منتظم وريتشاردسون المحظوظ) وتفكيك أعمى لاسترداد الصورة الأصلية من الصور غير الواضحة والصاخبة. مطلوب PSF (وظيفة انتشار النقطة) لأداء عملية deconvolution. تم استخدام برنامج MATLAB في هذه الدراسة كأداة مناسبة لمعالجة الصور. تعد نسبة الذروة إلى الإشارة (PSNR) وتشابه المؤشر الهيكلي (SSIM) هما أداتان رئيسيتان لفحص جودة الصورة. أظهرت النتائج أن المرشح المنظم كان أسلوبًا فعالًا لاسترجاع الصورة بالمعلومات السابقة حول PSF وللدرجات المختلفة من الضبابية كما حقق اكثر قيمة لـ(PSNR) وافضل (SSIM). لم تنجح تقنية إزالة التشويش الأربعة هذه في استعادة الصورة الأصلية من الصورة بتشويش Gaussian.

الكلمات الدالة: صاخبة، طمس، فك التغويش، ماتلاب، وينر.

1.INTRODUCTION

Different areas use and benefit from image processing, i.e., a subset of digital signal processing [1]. Digital image processing utilizes computer technology to segment, recover, improve, and eliminate noise from images [2, 3]. Artificial intelligence, programming, and computer science can be used in digital image processing [1]. The quality of an image is one of the major issues in this area of research because, in modern society, images constitute an essential component of our daily life. This study aims to improve image quality by reducing Gaussian blur [4]. Blurred is a significant factor in image deterioration and lowers image quality. Air noise and improper camera positioning cause image blur. Noise degrades the acquired image in addition to the blur effects. With many applications, it might be challenging to remove the blur from an image [5]. Image deblurring is a procedure that uses a mathematical model to eliminate blur or noise from images to recover high-quality images. There are numerous uses for image deblurring in consumer photography [4]. This paper investigated how the image was blurred with different degrees of blurring. Also, it examined the deblurring images using four algorithms utilizing MATLAB program, and PSNR and SSIM were calculated for each technique to indicate the image quality. Then, the noise was added with different variations to examine these four algorithms. Since visual blur is a frequent problem, it can be challenging to eliminate in many circumstances. Due to this issue, numerous academics have been trying to determine the best method for deblurring and restoring an image [6]. A method for deblurring photographs taken by a robotic system in real-time has been proposed by Kim and Ueda [7], Deblurring is performed by combining a dynamics-based technique with parallel computing, allowing deblurring. Although existing techniques have recovered a blurred image satisfactorily, they are unsuitable for real-time applications. Gupta and Shantaiya [8] proposed different filters and algorithms, i.e., the Wiener filter, an improved Lucy-Richardson deconvolution algorithm, and an inverse filter. The filter comparison offered various parameters that determine the image quality with the optimum outcomes. Yang et al. [9] proposed a blind deblurring method to predict a blur kernel. For usage as a reference image, a filter was suggested to make edges in a blurred image more distinct. This reference image was used to estimate the blur kernel. The calculated blur kernel was then used to deconvolve the blurred image, introducing a depth map. Belyaev and Fayolle [10] proposed iterative techniques to restore the clean image. They concluded that the suggested systems might be used to invert non-linear filters and deal with image deblurring issues and were competitive with current de-filtering techniques. Sharma and Shukla [11] presented some blur detection methods, including Edge sharpness analysis, Low-directional high-frequency energy, and blind image deconvolution. They found that much more effort must be made in the future to create a flawless and successful blur detection method. An effective blind deconvolution technique based on noise removal and edge enhancement was proposed by Cai et al. [12] to reduce noise and improve edge information, and better trilateral filtering was employed. The blur kernel estimation process also used the IFISTA approach. Shin et al. [5] suggested the Dual-Deblur technique using two blurred photos to create a single sharp image. An adaptive L2 SSIM loss was also suggested to improve structural characteristics and pixel accuracy. Numerous tests demonstrate that this strategy outperformed earlier ones in both qualitative and quantitative evaluations. Based on the above-studied techniques to deblur the image, the importance of this study is to investigate the blind and non-blind deconvolution techniques as restoration methods to deblur the image. Also, this study examines the effect of these

techniques if the noise is added to the blurred image. This study utilized MATLAB code in terms of PSNR and SSIM, the two essential tools used to indicate image quality. The rest of the paper is summarized: Section 2 describes the theoretical basis, Section 3 describes the experimental procedure, Section 4 presents the results and discussion, and Section 5 presents the conclusion.

2.THEORETICAL BASIS

2.1.Digital Image Processing Overview
Every scientist and engineer now has access to digital image processing due to the incredible advancements in computer technology over the past 20 years [13]. Image segmentation, noise reduction, enhancement, encoding, compression, and restoration are all parts of digital image processing, also called computer image processing. A digital image is represented by the expression $f(x, y)$, in which x and y represent the pixel coordinates or picture element and the intensity value, respectively [14]. Features of Digital Image processing include flexible processing, a sizable compression space, high processing resolution, and various applications [2]. Image blurring is a type of bandwidth reduction on an ideal image. An improper image production process can result in image blurring, which is Blur that frequently causes poor image quality when taking pictures. Most often, image blur results from camera shake brought on by the lens' dynamic movement during the capture process, movement of an object, out-of-focus because the camera lens could not set a proper angular position, and focusing and low-quality cameras [6,15]. Image blurring based on the degradation model, as shown in Fig.1.
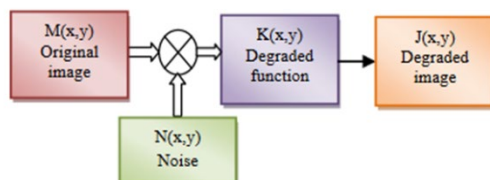

Fig. 1 Image Degradation Model [16].

The blurred image can be expressed according to the degradation model [16]:

$$J(x,y)=M(x,y) \times K(x,y)+N(x,y) \quad (1)$$

Where J(x,y) is the blurred image, M(x,y) is the original image, K(x,y): the distortion factor (PSF), and N(x,y): noise
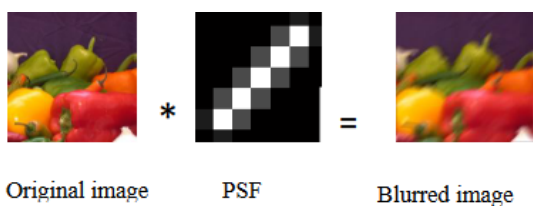

Fig. 2 Blurred Image Process [16].

There are six types of blurring [4]: Gaussian Blur, Average Blur, Motion Blur, Box Blur, Out of Focus Blur, and Atmospheric Blur. PSF: is how much a point of light is scattered or distorted by an optical system. The optical transfer function's inverse Fourier transform is the PSF [4].

3.EXPERIMENTAL PROCEDURE
Image deblurring is a common issue in low-level computer vision to restore a clear image from a blurred input image. Deep learning innovations have significantly advanced the solution to this issue, and numerous deblurring networks have been presented [17]. When an image-capturing procedure degrades the original image, image deblurring is a crucial step in restoration [18]. Images are captured in many different contexts, including everyday photography, astronomy, microscopy, medical imaging, and remote sensing; therefore, image deblurring and restoration are crucial to digital image processing [19].

3.1.Deblurring Techniques
In image processing, there are numerous methods for image deblurring. Four fundamental techniques are distinguished as follows [16]:
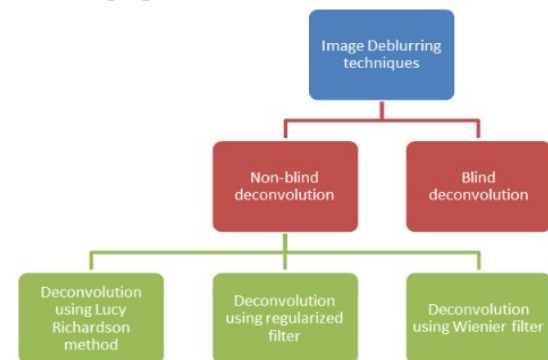

Fig. 3 Image Deblurring Classification [4].

Non-Blind Deconvolution: In this technique, prior knowledge of PSF is required to perform the process of deconvolution [16]. Non-blind deconvolution is classified as follows:

1-Deconvolution Using Weiner Filter
Norbert Wiener came up with the Wiener filter in the 1940s, first published in 1949. By comparing the amount of noise in a signal to an estimate of the intended noiseless signal, the Wiener filter seeks to reduce the signal's noise. Since the theory underlying a Wiener filter implies that the inputs are stationary, a Wiener filter is not an adaptive filter. The Wiener filter's objective is to remove noise that has distorted a signal. The Wiener filter is founded on a statistical methodology [20]. Prior knowledge of the point spread function's parameters is necessary for this strategy. A blurred image is deblurred using the deconvwnr function. Wiener deconvolution can be used effectively when the additive noise and image's frequency characteristics are at least substantially known.

Without noise, the wiener filter is reduced to an ideal inverse filter [16].

2- Deconvolution Using a Regularized Filter

It utilizes a regularizing filter for deblurring purposes. This approach is functional when there is little noise information available. Less prior information is needed for deconvolution when using regularized filtering [16]. The constrained least squares filter solves the Wiener filter's problems (of the original image's power spectrum computation) and inverse filter (noise amplification). A smoothness measure eliminates the noise sensitivity issue for the best possible restoration. The problem parameters limit the restoration [21].

3- Deconvolution Using Lucy-Richardson

One of the most often used deblurring methods in image processing is the Lucy-Richardson algorithm since it does not consider the kind of noise impacting the image. The Lucy-Richardson algorithm is an iterative algorithm in which no data from the initial clean image is required. This technique can be employed effectively when the PSF is known and no noise information is available [16]. This method showed reliability in improving the image quality, which depends on the iteration count, which is the key determinant of the image's quality [22, 23].

4- Blind Deconvolution

When the blur kernel is unknown, the challenge of recovering a sharp version of an input hazy image is known as blind image deconvolution. In numerous applications; including astronomical speckle imaging, remote sensing, and medical imaging [24]; blind deconvolution is used to restore images. The blind deconvolution approach is useful when the blur operator (PSF) is unknown since it operates blindly. It will simultaneously recover the image and the associated PSF [16]. The fundamental benefit of this technique is that it allows us to deblur an image without the need for prior knowledge of the blurring characteristics that other techniques entail, such as PSF and noise [11].

3.3. Experimental Sets

The image was blurred in this study using MATLAB code [25]. Then, four deblurring techniques were applied to the blurred image to investigate the impact of the non-blind and blind deconvolution techniques on the blurred image and noisy/blurred image to examine which technique achieved the best deblurring improvement in PSNR and SSIM. This methodology was done in several cases for each of the deblurring techniques. The algorithm steps are as follows:

Case 1: blurring the image with blurring angle = 60° and 90°

Case 2: The noise was added to the image with a Variance of Gaussian noise = 0.05, and the same four deblurring techniques were applied.

Case 3: The noise was added to the blurred image with a Variance of Gaussian noise = 0.05 and 0.3, and the same four deblurring techniques were applied.

MATLAB code for each filter was written. The results obtained from the simulation are presented in the following section.
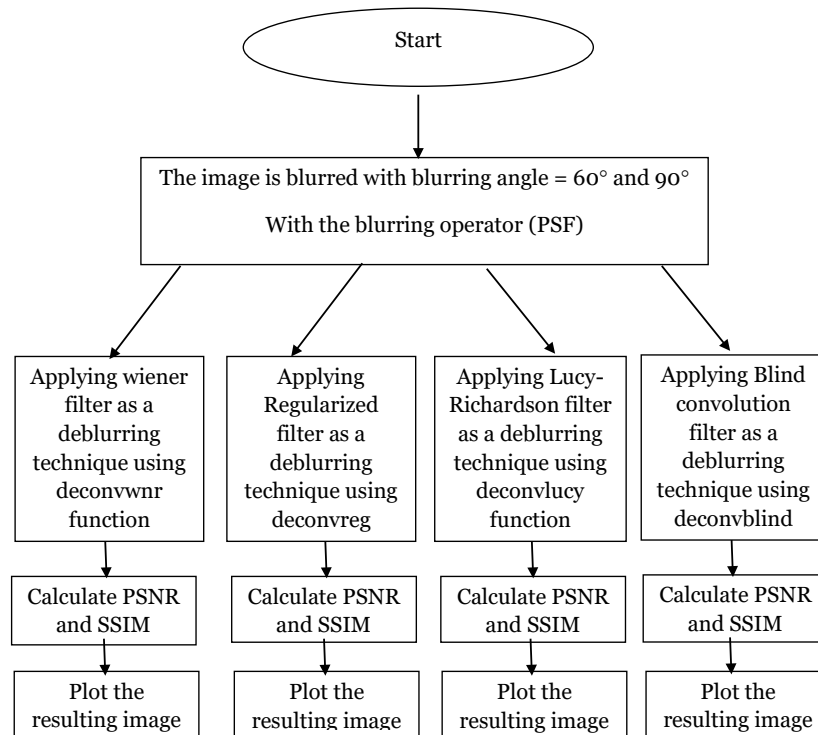

Fig. 4 Case 1 Flow Chart.

4. RESULTS AND DISCUSSION

Four deblurring techniques (non-blind deconvolution and blind deconvolution) were utilized to deblur the image with an angle of blurring = 60°, as shown in Fig. 5. As shown in Fig. 5, the regularized filter was the best technique to retrieve the original image from the blurring image. Four deblurring techniques (non-blind deconvolution and blind deconvolution) were utilized to deblur the image with an angle of blurring = 90°, as shown in Fig.6. As shown in Fig. 6, the regularized filter acted as the best technique to retrieve the original image from the blurring image, and the Weiner filter performed better to retrieve the original image from the blurred image when the blurring image was increased to 90°. Then, the Gaussian noise was added to the original image with a variation of (var = 0.05), and the four deblurring techniques were applied. The results are shown in Fig. 7. As shown in Fig. 7, the regularized filter was the worst filter to retrieve the original image from the noisy image, while it was the best filter to deblur the image. Then, the noise was added to the blurred image to examine the impact of four deblurring techniques on the blurred image with noise with Gaussian noise variation = 0.05 and 0.3, as shown in Figs. 8-9.
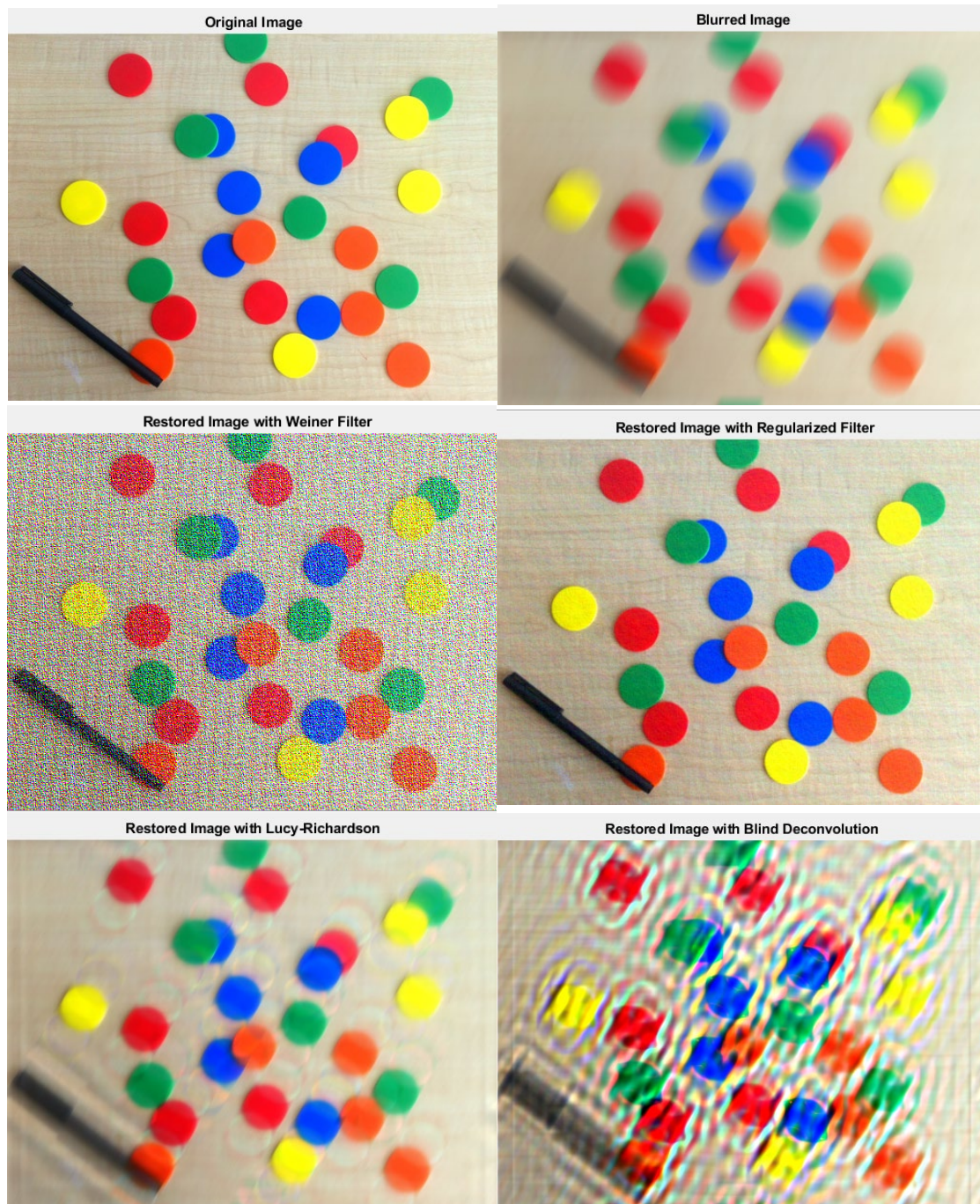

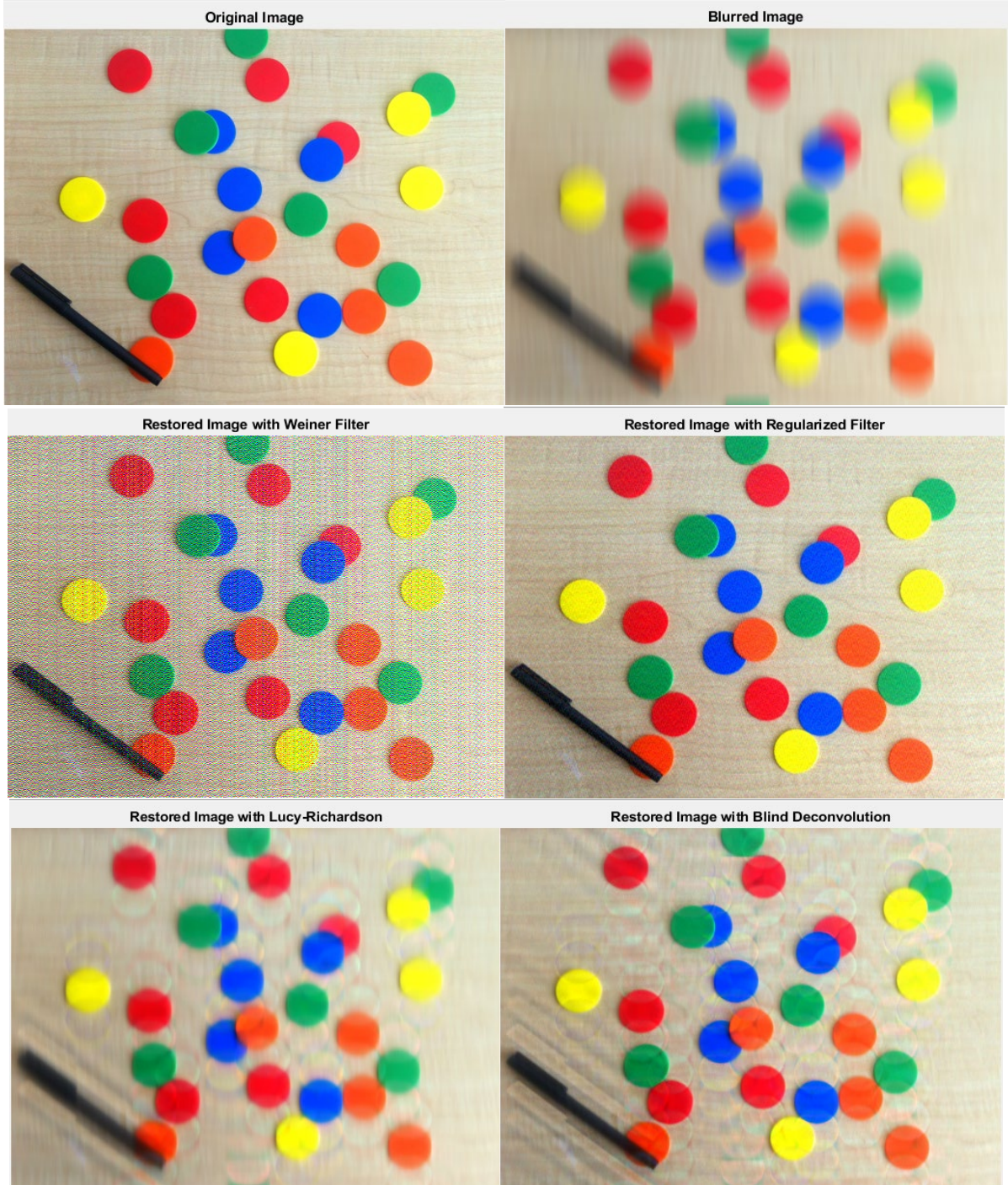**Fig. 5** Four Deblurring Techniques (Blurring Angle = 60°).

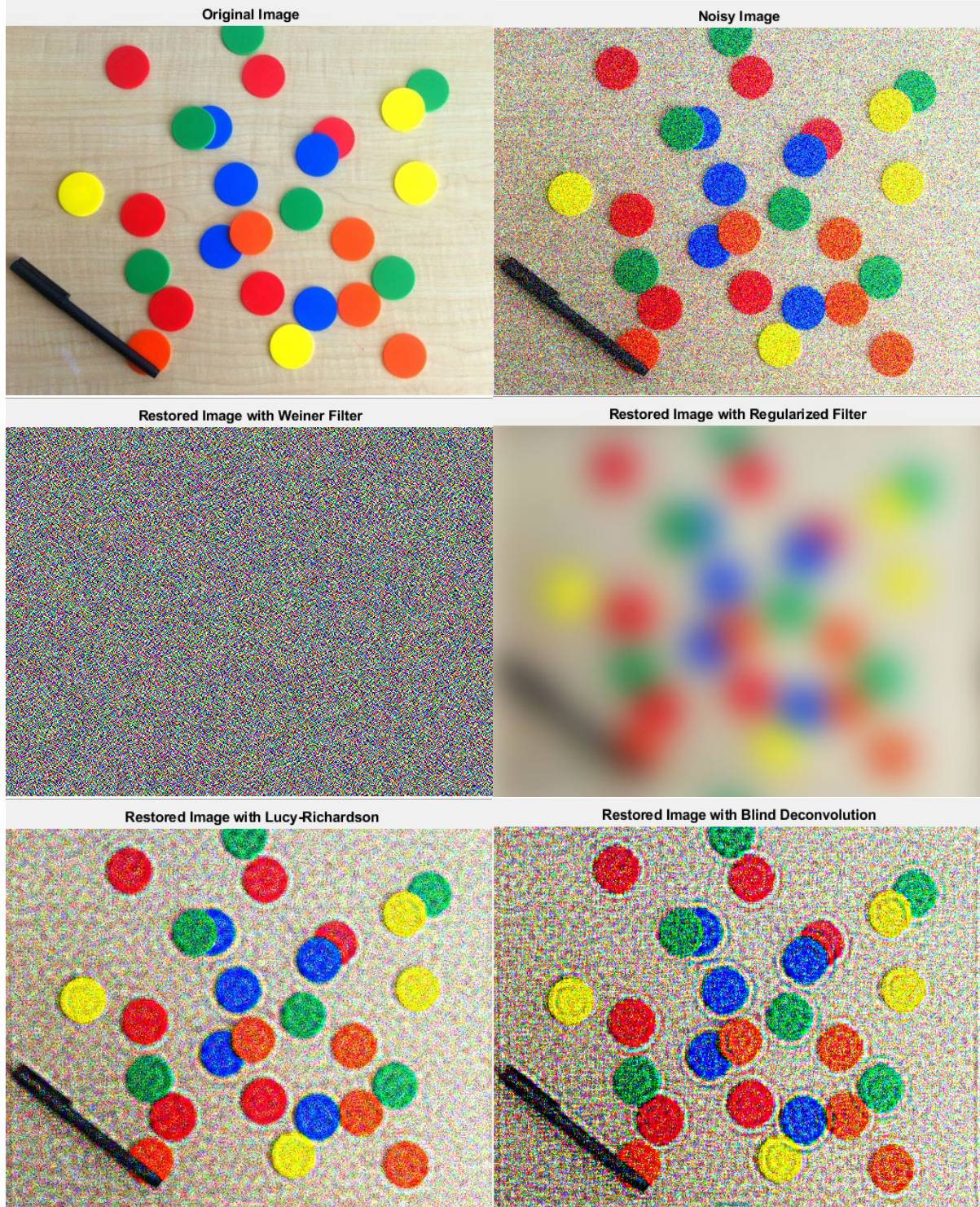**Fig. 6** Four Deblurring Techniques (Blurring Angle = 90°).

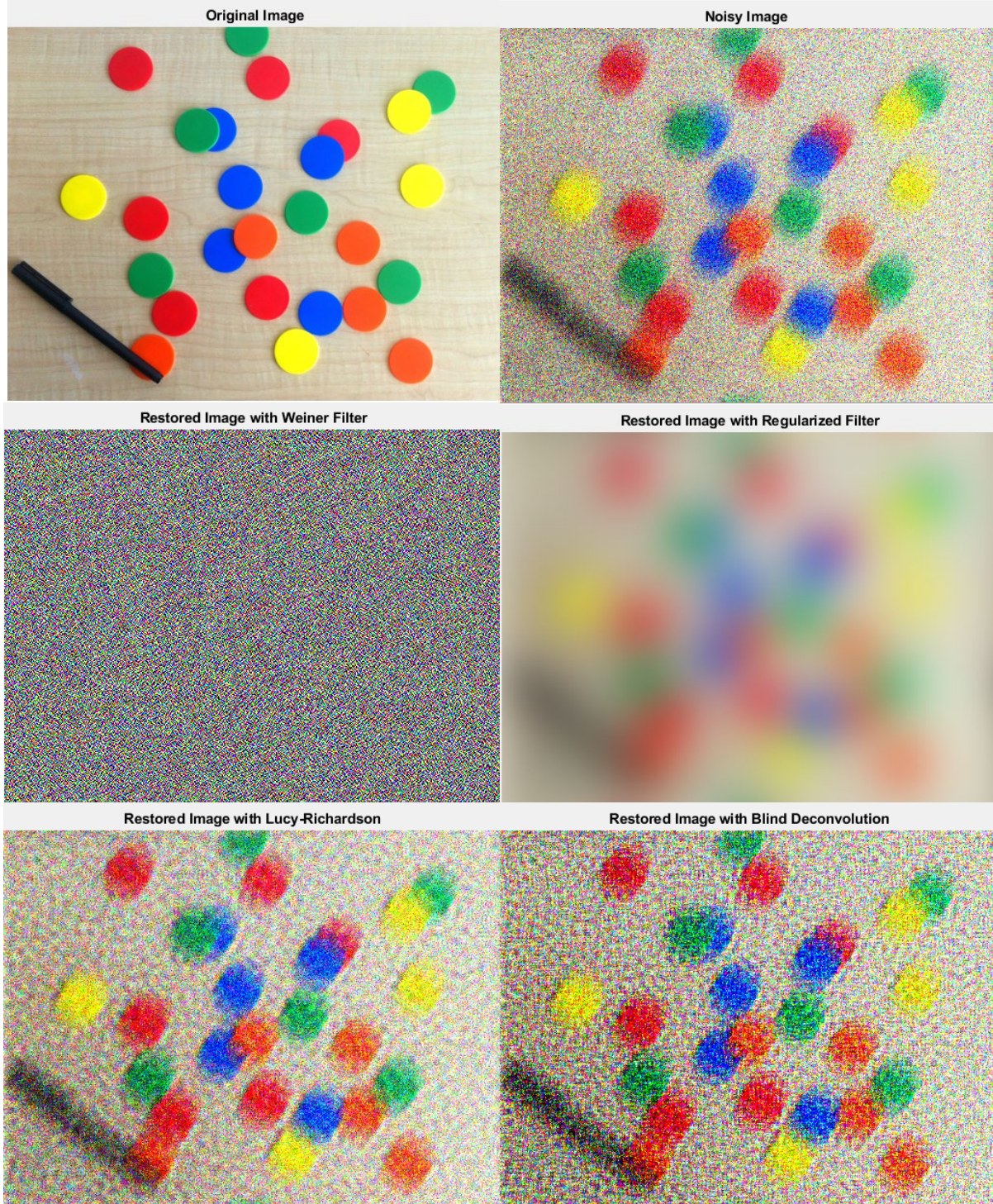**Fig. 7** Four Deburring Techniques for the Noisy Image with (Var = 0.05).

Fig. 8 Four Deburring Techniques for the Blurred/Noisy Image with (Var = 0.05).
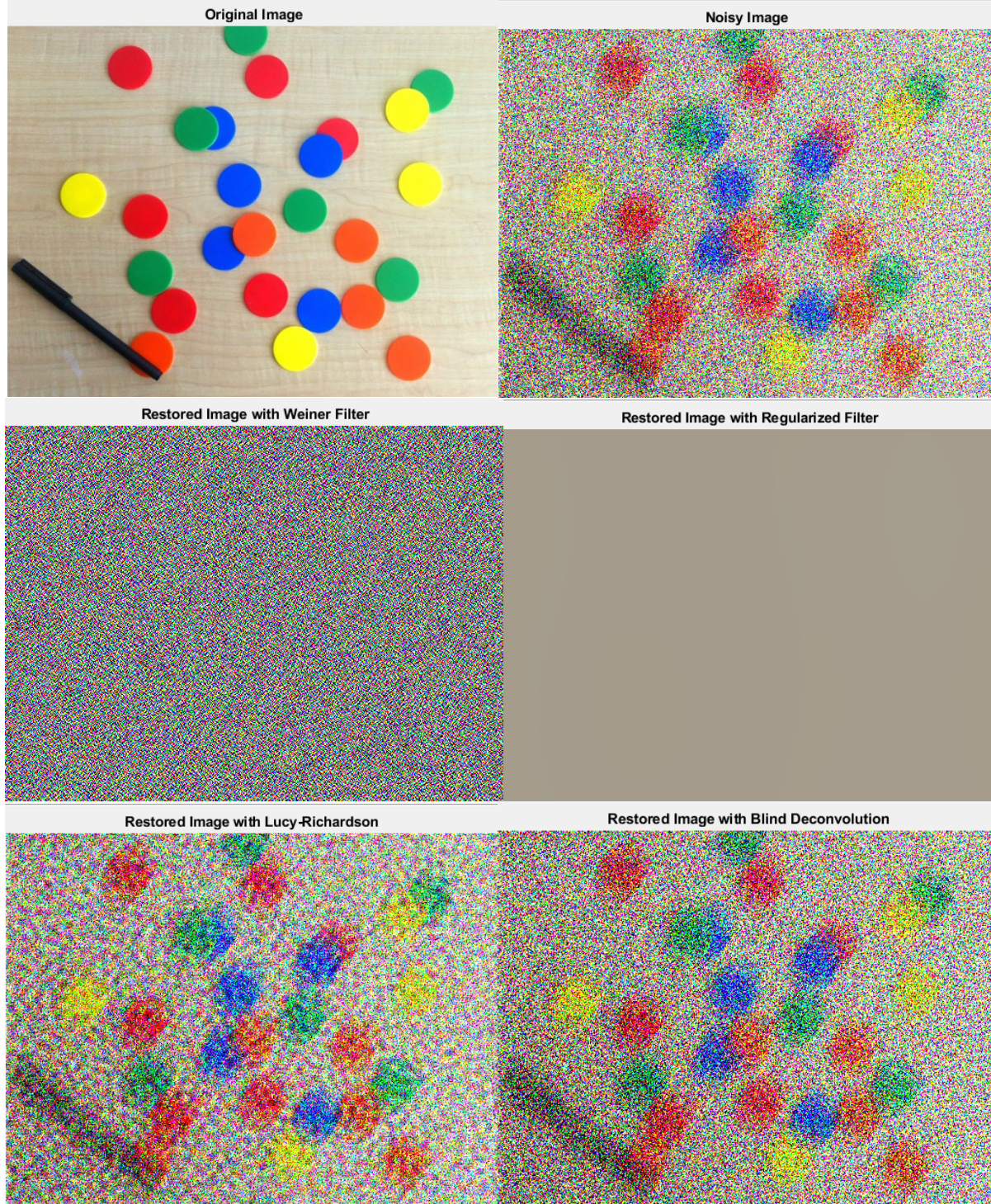
Fig. 9 Four Deburring Techniques for the Blurred/Noisy Image with (Var = 0.3).

As shown above, four deblurring techniques failed to recover the original image from the blurred/noisy image. Peak Signal to Noise Ratio (PSNR) and structural index similarity (SSIM) are two measuring tools that are widely used in image quality assessment. These tools were calculated for the blurred image with two degrees (60° + 90°) and the blurred image with noise with different variations (0.05 and 0.3), as shown in Table 1. As shown in Table 1, for the blurred image, the regularized filter performed

the largest PSNR, indicating a better image quality and best SSIM because when SSIM is closer to 1, it indicates better image quality. Lucky-Richardson also performed better in PSNR and SSIM for different blurring degrees. For blurred/noisy images, the four deblurring techniques would not achieve good PSNR and SSIM; however, the lucky-Richardson performed the largest PSNR when the Gaussian noise variation was 0.05.

Table 1 Performance Analysis.

Blur Type	Restoration Type	PSNR	SSIM
Gaussian Blur (Blurring degree = 60°) with no noise	No filter	22.1603	0.8798
Gaussian Blur (Blurring degree = 60°) with no noise	Weiner Filter	9.8560	0.1710
Gaussian Blur (Blurring degree = 60°) with no noise	Regularized Filter	32.0595	0.9388
Gaussian Blur (Blurring degree = 60°) with no noise	Lucky-Richardson	26.4204	0.9259
Gaussian Blur (Blurring degree = 60°) with no noise	Blind Convolution	16.6385	0.5784
Gaussian Blur (Blurring degree = 90°) with no noise	No filter	22.5410	0.8852
Gaussian Blur (Blurring degree = 90°) with no noise	Weiner Filter	11.9026	0.2389
Gaussian Blur (Blurring degree = 90°) with no noise	Regularized Filter	29.4139	0.8902
Gaussian Blur (Blurring degree = 90°) with no noise	Lucky-Richardson	26.9661	0.9311
Gaussian Blur (Blurring degree = 90°) with no noise	Blind Convolution	29.5917	0.9417
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.05)	No filter	13.3894	0.2657
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.05)	Weiner Filter	4.7787	0.0031
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.05)	Regularized Filter	5.2159	0.0162
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.05)	Lucky-Richardson	12.0077	0.2258
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.05)	Blind Convolution	6.5722	0.1059
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.3)	No filter	8.4885	0.1125
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.3)	Weiner Filter	4.7801	0.0035
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.3)	Regularized Filter	4.9784	0.0082
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.3)	Lucky-Richardson	7.7356	0.1088
Gaussian Blur (Blurring degree = 60°) with Gaussian noise (V=0.3)	Blind Convolution	7.1568	0.0932

5. CONCLUSIONS

The quality of an image is one of the major issues in this area of research because images constitute an essential component of our daily life. Blurred is a significant factor in image deterioration and lowers image quality. Air noise and improper camera positioning cause image blur. Image deblurring is a common issue in low-level computer vision to restore a clear image from a blurred input image. This study examined the impact of non-blind deconvolution (Weiner filter, Regularized Filter, and lucky- Richardson) and Blind deconvolution techniques to deblur the image and to examine the impact of these deblurring techniques on the noisy/blurred image in terms of PSNR and SSIM, which are the two major important performance evaluation parameters. MATLAB program was utilized in this study in three cases. The image was blurred in the first two cases with the blurring degrees 60° and 90°, and the four deblurring techniques were applied. The results showed that the Wiener Filter was faster than Richardson Lucy; however, it can produce negative values and ringing artifacts. In this study, the Regularized technique achieved the largest PSNR and best SSIM, making it an effective tool to restore the original image. Lucky-Richardson also performed better in PSNR and SSIM for different blurring degrees. In the third case, Gaussian noise was added to the blurred image with two noise variations, i.e., 0.05 and 0.3. The results showed that these blind and non-blind deconvolution techniques could not retrieve the original image from the blurred/noisy image. These tools also achieved lower PSNR and SSIM; however, the lucky-Richardson performed the largest PSNR when the Gaussian noise variation was 0.05. In future work, more iterations could be applied to get the best results, and using median and average filters will be an efficient technique to retrieve the original image from the noisy image.

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