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Remove Blur Image using Bi-Directional Akamatsu Transform and Discrete Wavelet Transform

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Abstract.
Purpose: Image is an imitation of everything that can be materialized, and digital images are taken using a machine. Although digital image capture uses machines, digital images are not free from interference. Image restoration is needed to restore the quality of the damaged image.
Methods: Bi-directional Akamatsu Transform is proven to have an effective performance in reducing blur in images. Meanwhile, Discrete Wavelet Transform has been widely used in digital image processing research. We had been investigated the image restoration method by combining Bi-directional Akamatsu Transform and Discrete Wavelet Transform. Bi-directional Akamatsu Transform applied in Low-Low (LL) sub-band is the Discrete Wavelet Transform decomposition image most similar to the original image before decomposing. In this study, there are still shortcomings, including the determination of the values of N, up_enh, and down_enh, which are still manual. Manually setting the three values makes the Bi-directional Akamatsu Transform method not get the best results. With the use of machine learning methods can get better restoration results. Further testing is also needed for a more diverse and robust blur. The image data has a resolution of 256x256, 512x512, and 1024x1024. The image will be directly converted to a grey-scale image. The converted image will be given an attack model: average blur, gaussian blur, and motion blur. The image that has been attacked will apply two restoration methods: the proposed method and the Bi-direction Akatamatsu Transform. These two restoration images will then be compared using PSNR.
Result: The average PSNR value from the restoration of the proposed method is 0.1446 higher than the average PSNR value from the restoration of the Bi-directional Akamatsu Transform method. When we compare it with the average PSNR value of the Akamatsu Transform restoration method, the average PSNR of the proposed method is 0.2084.
Value: The combination of DWT and akamatsu transform results produce good PSNR values even though they have gone through the blurring method in image restoration.

Keywords: Digital Image, Restoration, Akamatsu Transform Bi-directional, Akamatsu Transform, Discrete Wavelet Transform
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INTRODUCTION

Image is an imitation, resemblance, or representation of people, places, objects, and everything that can be materialized [1]. The image is a painting since prehistoric times. But along with the development of human civilization, the form of an image is no longer just a painting [2]. The medium used for the image is starting to vary with the technology. The mediums used range from canvas and paper to digital. Digital image is an image taken using a machine based on sampling and quantization. Digital images are not free from interference, even if taken using a machine. Light, noise, blur, and others cause the image quality to decrease [3]. These things cause the information contained in the image to be reduced. Blur can be caused by a dirty camera lens [4]. The camera or a moving object can also cause it. Image restoration is needed to restore the quality of the damaged image. In the image restoration process, there are various methods, such as Lucy-Richardson [5], Wiener Filter [6], Discrete Wavelet Transform [7]–[9], Discrete Cosine Transform [10], Fourier Transform [11], Akamatsu Transform [6] and Bi-directional Akamatsu Transform [12].

Research using the Wiener algorithm proposed by [13] to restore blurry images. The image restoration process is carried out with two sub-processes. The first part degrades the image quality by adding noise and blur, and the second part removes noise and blur from the degraded image and restores the original image.

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This study uses the Non-Blind Restoration technique, which is a technique that assists in the reconstruction of the original image from the degraded image when the way the image is degraded is known. The method used in implementing the restoration technique is the iterative method. The modified iterative Wiener filter used in this study is an efficient method of restoring degraded medical images. The MSE value of the restored image decreases with an increasing number of iterations until the results converge. Most of the convergence occurs after ten iterations. In the end, the best result of the restored image is obtained when setting the parameter equal to one. In another study by [14], the efficiency of image restoration methods was compared for various blurry space images. The methods compared in this study are Kalman and Wiener filters. The image used in this study is assumed to have no noise. The image is applied motion blur, which has an average length equal to 5. Zero mean Gaussian noise, known as standard deviation, is also added. The following process is image restoration using wiener and Kalman filters on the tested image. From the results of the experiments, the Kalman filter is better than the Wiener filter in restoring blur images that are affected by space-variant blur.

Research [15] correcting or restoring images' blur using the Akamatsu Transform method. Akamatsu Transform is a technique Norio Akamatsu proposed to create differential and integral signals from the given original signals. The resulting integral from the Akamatsu Transform is similar to that of a low-pass filter. In contrast, the differential is assumed to be the high-frequency components of the original image. So that the characteristics of the original image can be seen in the differential. This method has a reasonably practical restoration result in restoring the image. But this method of restoring a stronger blur image requires further research to determine the appropriate downEnh and upEnh.

In a study [16], the blurred image restoration used the Bi-directional Akamatsu Transform method. This method is a research development of the Akamatsu Transform method [15]. The development of this method is that this method performs the Akamatsu Transform horizontally or in the direction of the X-axis and vertically or in the direction of the Y-axis. While the Akamatsu Transform method proposed in research [16] only performs horizontally or in the direction of the X-axis. The restoration method's results in this study reduced the blur effect on the image. Based on the experiments conducted in the study, the proposed method reduces the blur effect better than the method in the study [15]. However, in this method, the determination of downEnh and upEnh is still done manually.

Wavelet Transform has been widely used in digital image processing and [12] pattern recognition. Discrete Wavelet Transform is a form of the wavelet transform. DWT, in decomposing the image, the image will be divided into four sub-bands, namely Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH). LL is a representation of the image and is the sub-band that is most similar to the original image before being decomposed. While the other three sub-bands, namely LH, HL, and HH, are variations of wavelets vertically, horizontally, and diagonally.

The proposed method is used to restore noise and blur images. The image will be decomposed using DWT. Then the results of the decomposition will be applied to the Akamatsu Transform. The LH sub-band uses the Akamatsu Transform vertically. The HL sub-band uses Akamatsu transform horizontally. And HH uses Akamatsu transform horizontally and vertically. The results of this restoration method do not change the characteristics of the original image significantly, but the noise in the image is reduced. For restoration results on blur, the image restoration method in [15] produces a more precise image than the restoration image of the proposed method. Bi-directional Akamatsu Transform is a technique developed based on the Akamatsu Transform [16] method. This method is proven to reduce blur in the image better than the Akamatsu Transform method.

This research will use two combined methods: Bi-directional Akamatsu Transform and Discrete Wavelet Transform. Bi-directional Akamatsu transform is used for the sub-band LL image, which is the DWT decomposition image most similar to the original image before decomposing. Testing the restoration results had been calculated by PSNR and compared with previous studies.

METHODS

Akamatsu Transform

Akamatsu transform is developed from integral and differential transformation [17]. Norio Akamatsu first developed and patented this transformation in 2006 [6]. This transformation is used in image processing to restore the overall blur image. Akamatsu transform can be applied to recognize sounds in vowels [15], [16], where the target signal is in the transformation. With the target signal, the result of the transformation will be divided into two parts, namely, the right side of the target signal and the left side. [18] The signal on the right of P(x,y) we define as VRS(x) and on the left as VLS(x). The target signal is used to determine the result of the transformation. To get the target signal, it is necessary to calculate the integral and differential values. The integral value can be calculated by equation (1).

$$A(x) = \frac{[AvrS_R(x) + AvrS_L(x)]}{2} \quad (1)$$

Where,

$A(x)$ = Akamatsu transform integral value
$AvrS_R(x)$ = Average of the intensity values to the right of the target signal
$AvrS_L(x)$ = Average of the intensity values to the left of the target signal

Discrete Wavelet Transform

The wavelet-based method is used to obtain robustness that also maintains the two data types being transformed, frequency and spatial information [19]. Signal transformation is another form of signal representation that does not change the information contained in the signal. The wavelet transform has two development series: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). Discrete Wavelet Transform (DWT) algorithm [20] is an image-processing algorithm that uses the same mathematical calculations as DCT [21]. DWT has the characteristics of the image decomposition model into four parts (subbands), namely LL, LH, HL, and HH [22]. Frequency L is Low, and H is High. DWT is also an orthogonal transform with a fast computational process [23]. Figure 1 illustrates the DWT sub-band decomposition. Decomposition on DWT can be done using (2) and (3).

$$\Phi_{j,a,b}(x,y) = 2^{\frac{j}{2}}\varphi(2^j -, 2^j - a, 2^j y - b) \quad (2)$$

$$\Psi^i_{j,a,b}(x,y) = 2^{\frac{j}{2}}(2^j - a, 2^j - a, 2^j y - b), i = \{H, V, D\} \quad (3)$$

Where,

i = *wavelet* {LL, LH, HL, HH}
a,b = image size

LL	HL
LH	HH

Figure 1. Sub-band decomposition on DWT

Reconstruction is carried out by inverse DWT using the equation as shown in (4).

$$\begin{aligned} f(x,y) = {} & \frac{1}{\sqrt{ab}} \sum_a \sum_b w_\varphi(j_0, a, b)\varphi_{j_0,a,b}(x,y) \\ & + \frac{1}{\sqrt{ab}} \sum_{i=H,V,D} \sum_{j=jo}^{\varpi} \sum_a \sum_b w^i_\psi(j_0, a, b)\Psi^i_{j_0,a,b}(x,y) \end{aligned} \quad (4)$$

Where,

i = *wavelet* {LL, LH, HL, HH}
a,b = image size

Preprocessing

The image data collected cannot be directly used in the restoration process. The data collected will go through a preprocessing stage, including conversion and application of the attack model. After the data has gone through both stages, the data can be used for research. Uniformity of the type of image color map is required to eliminate the computational and processing burdens of RGB, binary, and grey-scale images. To simplify processing, the collected image data will be converted into a grey-scale image. The image used for research will be given two attack models before restoration. The images are given average blur, gaussian blur, and motion blur. After the images used for research are attacked, these images will be used in the proposed method's restoration process.

Method

Figure 2 shows the proposed method of this study. In this study, the image is given blur attacks, namely average blur, motion blur, and gaussian blur. The image given a blurred attack will be decomposed using DWT. The steps of the restoration process are described as follows:

1) The image given a blurred attack will be decomposed using DWT to get the LL, LH, HL, and HH sub-bands.
2) The LL sub-band will be applied using the Bi-directional Akamatsu Transform method to obtain the LL sub-band as a result of restoration.
3) The Inverse DWT process was carried out using LL restoration results, LH, HL, and HH.
4) The image resulting from the Inverse DWT process is the image resulting from the restoration of the proposed method.

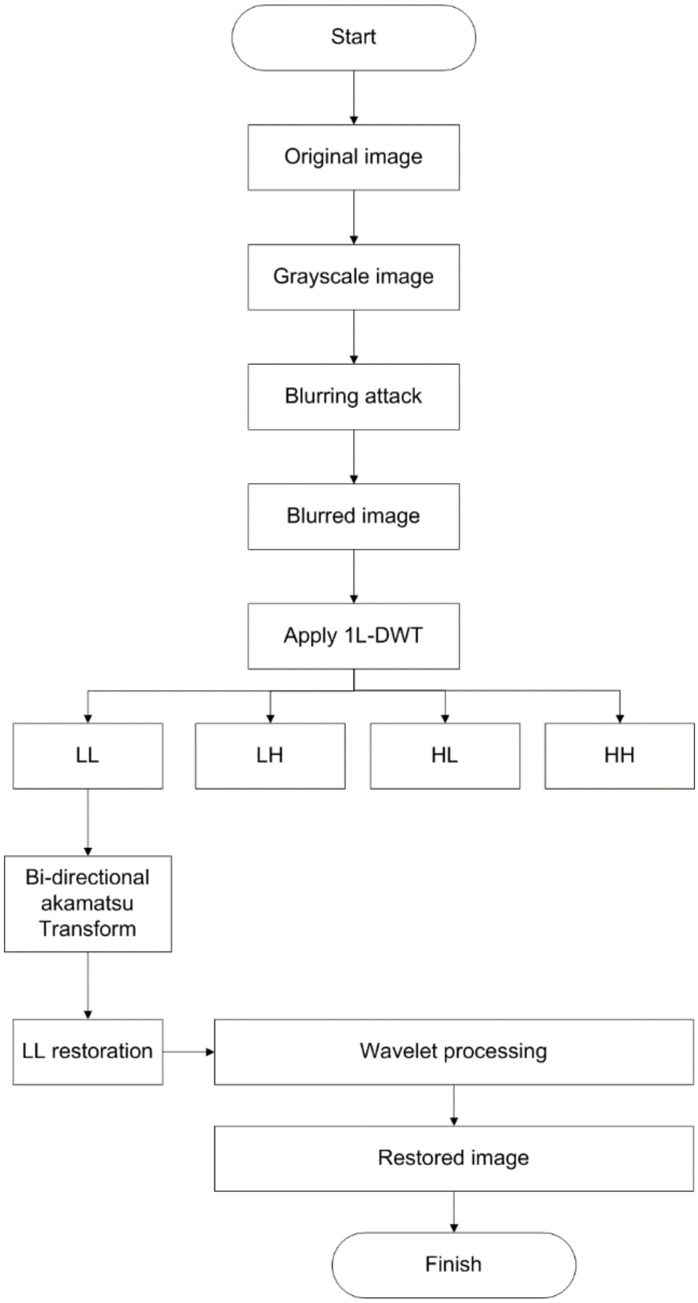

Figure 2. Proposed Method

Experiment

The restoration process was carried out using the MATLAB application. In this research, 20 images have been applied, where each image has three different pixel sizes, and among the selected images, there are color and grayscale images. The image data used has a resolution of 256x256, 512x512, and 1024x1024, as shown in Figure 3. Dataset taken from Irawan et al. [16], Karungaru et al. [15], Wellia [8], Eko Hari [24], and also https://sipi.usc.edu/database/. The image will be directly converted to a grey-scale image. The converted image will be given an attack model, namely average blur, gaussian blur, and motion blur with their respective intensities, on disc two or N=2. The image that has been attacked will apply two restoration methods: the proposed method and the Bi-direction Akatamatsu Transform. These two restoration images will then be compared using PSNR.

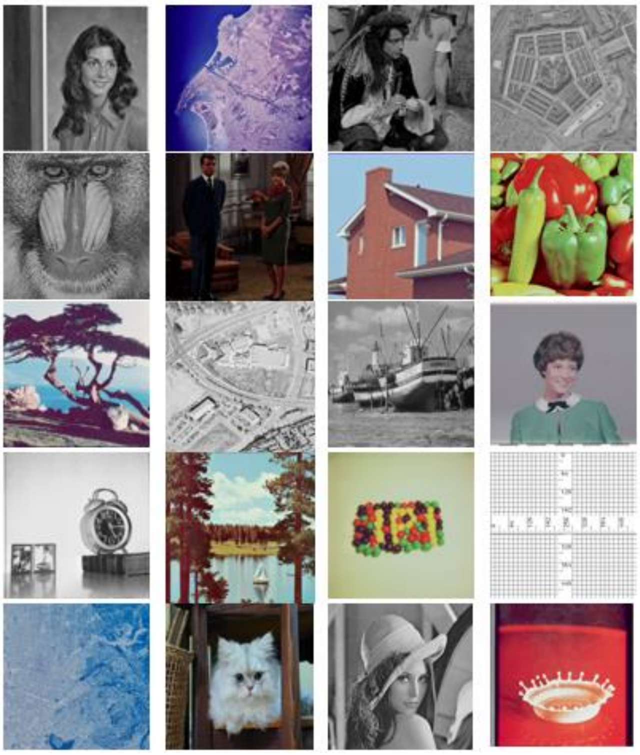

Figure 3. Original Images

Evaluation

The evaluation process will be carried out by looking at the PNSR value of the restoration. The PSNR value of the proposed method will be compared with the PSNR value of the restoration in studies [16] and [15]**.**

RESULT AND DISCUSSION

Table 1 shows the average PSNR value of the proposed method has a higher value than the methods [15] and [16]. The average PSNR value of the proposed method is 0.0641 higher than the average value of the method [16]. When compared with the average value of the method [15], the average PSNR value of the proposed method is higher by 0.1576. The PSNR values of the three methods are derived from restoring the average blur filter image with a constant H of 1. All three restoration methods use the same N, which is 2.

Table 1. PNSR value of restoration with N = 2 for average blur

Image	Resolution	PSNR		
		Proposed Method	Irawan et al [16]	Karungaru et al [15]
256_1.tiff	256x256	26,7420	26,6234	26,5104
256_1_reverse.tiff	256x256	26,7420	26,6234	26,5104
256_1_90.tiff	256x256	26,7420	26,6234	26,4276
256_1_180.tiff	256x256	26,7420	26,6234	26,5104
256_1_270.tiff	256x256	26,7420	26,6234	26,4276
256_2.tiff	256x256	25,0440	24,9643	24,8958

256_2_reverse.tiff	256x256	25,0440	24,9643	24,8958
256_2_90.tiff	256x256	25,0440	24,9643	24,8784
256_2_180.tiff	256x256	25,0440	24,9643	24,8784
256_2_270.tiff	256x256	25,0440	24,9643	24,8958
256_3.tiff	256x256	23,1713	23,1007	23,0558
256_3_reverse.tiff	256x256	23,1713	23,1007	23,0558
256_3_90.tiff	256x256	23,1712	23,1007	23,0534
256_3_180.tiff	256x256	23,1713	23,1007	23,0534
256_3_270.tiff	256x256	23,1712	23,1007	23,0558
256_4.tiff	256x256	25,9479	25,8442	25,7605
256_4_reverse.tiff	256x256	25,9478	25,8442	25,7605
256_4_90.tiff	256x256	25,9478	25,8442	25,7828
256_4_180.tiff	256x256	25,9478	25,8442	25,7828
256_4_270.tiff	256x256	25,9479	25,8442	25,7605
512_1.tiff	512x512	25,3793	25,2731	25,1964
512_1_reverse.tiff	512x512	25,3793	25,2731	25,1964
512_1_90.tiff	512x512	25,3793	25,2731	24,9477
512_1_180.tiff	512x512	25,3793	25,2731	24,9477
512_1_270.tiff	512x512	25,3793	25,2731	25,1964
512_2.tiff	512x512	22,8806	22,8449	22,8021
512_2_reverse.tiff	512x512	22,8806	22,8449	22,8021
512_2_90.tiff	512x512	22,8806	22,8449	22,8047
512_2_180.tiff	512x512	22,8806	22,8449	22,8047
512_2_270.tiff	512x512	22,8806	22,8449	22,8021
512_3.tiff	512x512	25,9039	25,8042	25,7608
512_3_reverse.tiff	512x512	25,9039	25,8042	25,7608
512_3_90.tiff	512x512	25,9039	25,8042	25,7537
512_3_180.tiff	512x512	25,9039	25,8042	25,7537
512_3_270.tiff	512x512	25,9039	25,8042	25,7608
512_4.tiff	512x512	22,8082	22,8247	22,7671
512_4_reverse.tiff	512x512	22,8082	22,8247	22,7671
512_4_90.tiff	512x512	22,8082	22,8247	22,7112
512_4_180.tiff	512x512	22,8082	22,8247	22,7112
512_4_270.tiff	512x512	22,8082	22,8247	22,7671
1024_1.tiff	1024x1024	27,7022	27,6545	27,5767
1024_1_reverse.tiff	1024x1024	27,7022	27,6545	27,5767
1024_1_90.tiff	1024x1024	27,7022	27,6545	27,5842
1024_1_180.tiff	1024x1024	27,7022	27,6545	27,5842
1024_1_270.tiff	1024x1024	27,7022	27,6545	27,5767
1024_2.tiff	1024x1024	28,9933	28,9975	28,8319
1024_2_reverse.tiff	1024x1024	28,9933	28,9975	28,8319
1024_2_90.tiff	1024x1024	28,9933	28,9975	28,8135
1024_2_180.tiff	1024x1024	28,9933	28,9975	28,8135
1024_2_270.tiff	1024x1024	28,9933	28,9975	28,8319
Average		25,4573	25,3932	25,2997

Based on Table 2, the average PSNR value for the restoration of the proposed method has a higher value than the average value for the methods [15] and [16]. The average value of the restoration results of the proposed method has a higher value of 0.1977 than the average PSNR value of the method [16]. When compared with the average PSNR value of the method [15], the average PSNR value of the proposed method is 0.2632. The PSNR values of the three methods are derived from the restoration of motion blur filter images with a len of 5 and theta of 90. The three restoration methods use the same N, namely, 2.

Table 2. PSNR value of restoration with N = 2 for motion blur

Image	Resolution	PSNR		
		Proposed Method	Irawan et al [16]	Karungaru et al [15]
256_1.tiff	256x256	24,4816	24,2286	24,0711
256_1_reverse.tiff	256x256	24,4816	24,2286	24,0711
256_1_90.tiff	256x256	24,2614	23,9265	23,6958
256_1_180.tiff	256x256	24,4816	24,2286	24,0711

256_1_270.tiff	256x256	24,2614	23,9265	23,6958
256_2.tiff	256x256	23,4442	23,2011	23,1407
256_2_reverse.tiff	256x256	23,4442	23,2011	23,1407
256_2_90.tiff	256x256	23,6610	23,4340	23,3297
256_2_180.tiff	256x256	23,6610	23,4340	23,3297
256_2_270.tiff	256x256	23,4442	23,2011	23,1407
256_3.tiff	256x256	22,2299	22,0716	21,9888
256_3_reverse.tiff	256x256	22,2299	22,0716	21,9888
256_3_90.tiff	256x256	22,1678	22,0005	21,9113
256_3_180.tiff	256x256	22,1678	22,0005	21,9113
256_3_270.tiff	256x256	22,2299	22,0716	21,9888
256_4.tiff	256x256	24,4293	24,2819	24,2186
256_4_reverse.tiff	256x256	24,4293	24,2819	24,2186
256_4_90.tiff	256x256	23,8196	23,6485	23,5769
256_4_180.tiff	256x256	23,8196	23,6485	23,5769
256_4_270.tiff	256x256	24,4293	24,2819	24,2186
512_1.tiff	512x512	20,5274	20,3702	20,4013
512_1_reverse.tiff	512x512	20,5274	20,3702	20,4013
512_1_90.tiff	512x512	21,9390	21,7953	21,7593
512_1_180.tiff	512x512	21,9390	21,7953	21,7593
512_1_270.tiff	512x512	20,5274	20,3702	20,4013
512_2.tiff	512x512	22,0306	21,8723	21,8277
512_2_reverse.tiff	512x512	22,0306	21,8723	21,8277
512_2_90.tiff	512x512	22,0020	21,8431	21,7953
512_2_180.tiff	512x512	22,0020	21,8431	21,7953
512_2_270.tiff	512x512	22,0306	21,8723	21,8277
512_3.tiff	512x512	24,6454	24,4459	24,4023
512_3_reverse.tiff	512x512	24,6454	24,4459	24,4023
512_3_90.tiff	512x512	24,7147	24,5087	24,4660
512_3_180.tiff	512x512	24,7147	24,5087	24,4660
512_3_270.tiff	512x512	24,6454	24,4459	24,4023
512_4.tiff	512x512	20,5895	20,3994	20,3459
512_4_reverse.tiff	512x512	20,5895	20,3994	20,3459
512_4_90.tiff	512x512	21,2262	21,0444	20,9914
512_4_180.tiff	512x512	21,2262	21,0444	20,9914
512_4_270.tiff	512x512	20,5895	20,3994	20,3459
1024_1.tiff	1024x1024	26,0069	25,7956	25,7563
1024_1_reverse.tiff	1024x1024	26,0069	25,7956	25,7563
1024_1_90.tiff	1024x1024	25,6849	25,4530	25,4002
1024_1_180.tiff	1024x1024	25,6849	25,4530	25,4002
1024_1_270.tiff	1024x1024	26,0069	25,7956	25,7563
1024_2.tiff	1024x1024	25,7290	25,5335	25,4924
1024_2_reverse.tiff	1024x1024	25,7290	25,5335	25,4924
1024_2_90.tiff	1024x1024	25,5260	25,2755	25,1988
1024_2_180.tiff	1024x1024	25,5260	25,2755	25,1988
1024_2_270.tiff	1024x1024	25,7290	25,5335	25,4924
Average		23,4469	23,2492	23,1837

Based on Table 3, the average PSNR value for the restoration of the proposed method has a higher value than the average value for the methods [15] and [16]. The average value of the restoration results of the proposed method has a higher value of 0.1719 than the average PSNR value of the method [16]. Compared with the method's average PSNR value [15], the average PSNR value of the proposed method is 0.2043 higher. The PSNR values of the three methods are derived from the restoration of the Gaussian blur filter image with a sigma constant of 1. All three restoration methods use the same N, which is 2.

Table 3. PSNR value of restoration with N = 2 for gaussian blur

Image	Resolution	PSNR		
		Proposed Method	Irawan et al [16]	Karungaru et al [15]
256_1.tiff	256x256	26,0289	25,7490	25,7264
256_1_reverse.tiff	256x256	26,0289	25,7490	25,7264
256_1_90.tiff	256x256	26,0289	25,7490	25,5939

256_1_180.tiff	256x256	26,0289	25,7490	25,7264
256_1_270.tiff	256x256	26,0289	25,7490	25,5939
256_2.tiff	256x256	24,2879	24,0563	23,9967
256_2_reverse.tiff	256x256	24,2879	24,0563	23,9967
256_2_90.tiff	256x256	24,2879	24,0563	24,0437
256_2_180.tiff	256x256	24,2879	24,0563	24,0437
256_2_270.tiff	256x256	24,2879	24,0563	23,9967
256_3.tiff	256x256	23,0532	22,9166	22,8823
256_3_reverse.tiff	256x256	23,0532	22,9166	22,8823
256_3_90.tiff	256x256	23,0532	22,9166	22,8674
256_3_180.tiff	256x256	23,0532	22,9166	22,8674
256_3_270.tiff	256x256	23,0532	22,9166	22,8823
256_4.tiff	256x256	25,0106	24,9048	24,9032
256_4_reverse.tiff	256x256	25,0106	24,9048	24,9032
256_4_90.tiff	256x256	25,0106	24,9048	24,8284
256_4_180.tiff	256x256	25,0106	24,9048	24,8284
256_4_270.tiff	256x256	25,0106	24,9048	24,9032
512_1.tiff	512x512	21,8145	21,7574	21,6652
512_1_reverse.tiff	512x512	21,8145	21,7574	21,6652
512_1_90.tiff	512x512	21,8145	21,7574	21,8165
512_1_180.tiff	512x512	21,8145	21,7574	21,8165
512_1_270.tiff	512x512	21,8145	21,7574	21,6652
512_2.tiff	512x512	22,4364	22,2755	22,2537
512_2_reverse.tiff	512x512	22,4364	22,2755	22,2537
512_2_90.tiff	512x512	22,4364	22,2755	22,2608
512_2_180.tiff	512x512	22,4364	22,2755	22,2608
512_2_270.tiff	512x512	22,4364	22,2755	22,2537
512_3.tiff	512x512	25,0924	24,8971	24,8905
512_3_reverse.tiff	512x512	25,0924	24,8971	24,8905
512_3_90.tiff	512x512	25,0924	24,8971	24,8676
512_3_180.tiff	512x512	25,0924	24,8971	24,8676
512_3_270.tiff	512x512	25,0924	24,8971	24,8905
512_4.tiff	512x512	21,7048	21,5638	21,4784
512_4_reverse.tiff	512x512	21,7048	21,5638	21,4784
512_4_90.tiff	512x512	21,7048	21,5638	21,5903
512_4_180.tiff	512x512	21,7048	21,5638	21,5903
512_4_270.tiff	512x512	21,7048	21,5638	21,4784
1024_1.tiff	1024x1024	26,4702	26,2620	26,2764
1024_1_reverse.tiff	1024x1024	26,4702	26,2620	26,2764
1024_1_90.tiff	1024x1024	26,4702	26,2620	26,2053
1024_1_180.tiff	1024x1024	26,4702	26,2620	26,2053
1024_1_270.tiff	1024x1024	26,4702	26,2620	26,2764
1024_2.tiff	1024x1024	26,3633	26,1609	26,1846
1024_2_reverse.tiff	1024x1024	26,3633	26,1609	26,1846
1024_2_90.tiff	1024x1024	26,3633	26,1609	26,0869
1024_2_180.tiff	1024x1024	26,3633	26,1609	26,0869
1024_2_270.tiff	1024x1024	26,3633	26,1609	26,1846
Average		24,2262	24,0543	24,0219

Based on Table 4, using average blur got the same blur reduction. However, the difference between the three restored images is not very visible. So from a visual comparison, all three methods have the same ability to reduce blur. Whereas using motion blur, the image restored by the three methods has strengthened image characteristics and reduced blur. If the three methods are compared visually, the three methods have the same capabilities. That's because the images from the restoration of the three methods look similar, from 256x256 to 1024 resolution. Using Gaussian blur, image restoration results from the three methods have stronger image characteristics and reduced blur.

Table 4. A Comparison of Restoration results

Average blur			Motion blur			Gaussian blur		
Proposed	By [16]	By [15]	Proposed	By [16]	By [15]	Proposed	By [16]	By [15]

The visual differences in the restoration images of the three restoration methods are not very visible to the naked eye, as shown in Table 5. Our proposed method yields the highest PSNR against blurring filters. By implementing attack blur, namely average blur, motion blur, and Gaussian blur where we equate the intensity according to Irawan's research [16] with N=2 (disk 2) and Karungaru [15] with intensity xy2 (N=2). Thus it can be proven that the PSNR value we produce is slightly higher than the two studies above.

Table 5. The average PSNR value of the overall restoration

Type of blur filter	Average PSNR		
	Proposed	Irawan [16]	Karungaru [15]
Average	25,4573	25,3932	25,2997
Motion	23,4469	23,2492	23,1837
Gaussian	24,2262	24,0543	24,0219
Average Result	24,3768	24,2322	24,1684

CONCLUSION

This research combines two transformation methods, Bi-directional Akamatsu Transform and Discrete Wavelet Transform, to eliminate blur in the image. The restoration results prove that the three methods can reduce blur in the image. Visually, the image restoration of the proposed method [16] and method [15] looks similar. Therefore, the images from the restoration of the three methods need to be compared by PSNR. From the comparison table, the average PSNR value from the restoration of the proposed method is 0.1446 higher than the average PSNR value from the restoration method [16]. When compared with the average PSNR value of the restoration method [15], the proposed method's average PSNR value is 0.2084. The proposed method has a higher average PSNR value than the two methods because the Bi-directional Akamatsu Transform restoration method is not applied directly to the blurred image but to the LL sub-band, which is the result of decomposition of the blurred image using Discrete Wavelet Transform.

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