iBlurDetect: Image Blur Detection Techniques Assessment and Evaluation Study

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Abstract: The quality of images is essential in computer vision, image processing, and other related fields. Image restoration is one of the categories in image processing, where the quality of an image plays a vital role in the process. Blur detection is a pre-processing stage in image restoration. Using different blur detection techniques, the quality of an image can identify if blurry or not. This study aims to provide a comparative performance of the available state-of-the-art blur measure operators or blur detection techniques. Python 6.3 was used for testing and evaluating the blur detection techniques. Providing the confusion matrix, precision, recall, f-measure, accuracy, and execution time were used to compare blur detection techniques. In testing, the Gaussian kernel and threshold value were set to measure the performance of each technique. Provided on the evaluation results, in terms of accuracy rate, HWT leads the best result. Based on the computed scores, FFT got the highest precision score, while LAP got the highest recall score, and HWT got the highest f-measure score. In terms of the execution time, MLAP performs the fastest processing time among them all. Likewise, results of this study can use as resources before performing the image restoration.

1 INTRODUCTION

Image perform a significant role in technology as well as in the research domain. These images can applied in computer vision and image processing such as image representation (Cruz-Roa et al, 2013), object recognition and matching (Yadav and Singh, 2016), 3D scene reconstruction (Yang, Zhou and Bai, 2013; Fang, Tao and Jia-Lin, 2017), and motion tracking (Chen and Liu, 2018; Ancheta et al, 2018) to name a few. Images are produced to record or display important information.

The quality of an image contributes to the success of determining certain information that can used in different fields of research. In feature detection, for example, the recognition rate depends on the image quality(Dharavath et al, 2014).

Image quality can be degraded due to distortion during acquisition and processing. Some common factors may affect the quality of an image are contrast, noise, artifacts, and blurring (Su, Lu, and Tan, 2018). To address this issue, image recognition techniques are continuously being performed and improved (Sprawls, 1995).

Image blurring is a form of bandwidth reduction on an ideal image caused by an imperfect image construction procedure(Bovik and Gibson, 2000). Blur is the typical image downfall problem when capturing the photos. Image blur occurs in most cases of image deterioration resulting from defocusing or handshaking (Yang, Lin and Chuang, 2017).The reasons behind the output of blurry images are camera shaking due to dynamic movement of the lens during the process of capture, object movement, out-of-focus due to camera lens could not set a proper angle and focus, out-of-focus, and low-quality cameras (Dharavath et al, 2014) and (Su, Lu, and Tan, 2018).

Since image blur is a common issue, and it is, at times difficult to remove in many situations. Due to this problem, many researchers are working on finding the best way to de-blur the image and restore the blurred image (Bansal et al, 2017; Huang et al, 2019). Study (Bansal et al, 2017) stated that to maintain the quality of the image it is vital to detect and eliminate the blur from images.

Image processing techniques can use in the modificationof digital data for refining the image qualities with the aid of a computer system (Bansal et al, 2017).

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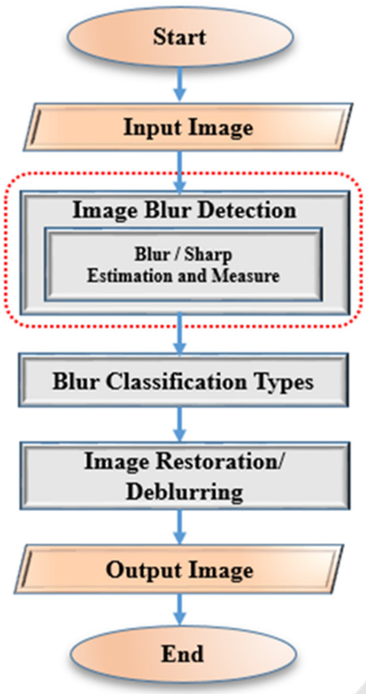

Figure 1: Flowchart of Image Blur Detection Framework.

Figure 1 shows the flowchart of image blur detection framework. The study of (Koik and Ibrahim, 2014), narrow down the researches available in public domain about blur images into three major processes: a) image blur detection, the initial process in improving the quality of the image that suffers from blur, b) blur classification, the second process of the research related to blur images. The goal of this process is to classify the blur areas according to their characteristics or types, and 3) image restoration, the third process, perform deblurring process based on their characteristics. This paper concentrates only on the stage of image blur detection that consider the blur/sharp estimation and measure which is enclosed in red-dotted lines in figure 1.

This paper focuses on the different blur detection techniques and aims to compare the performance of each one in terms of accuracy rate and execution time. Also, compare and analyze the existing techniques in identifying if the input image is blurred or sharp to achieve the best possible results.

The project's long term goal aims to maintain a comparable number of extracted feature points with a sharp image and to increase the number of correctly matched feature points of inputted blur image. The project groundwork lays on computer vision, and image processing notably features point detector. Blur detection techniques are useful in image blur detection because it is used as the preliminary process to detect specific regions that need for image restoration or deblurring process. As the primary step towards the goal of the project, we conducted a review and analysis of the different blur measure operators or state-of-the-art of image blur detector techniques.

This paper has been organized as follows. Section 2. Blur detection techniques. Section 3. Experimental methodology. Section 4. Deals with the results and discussions and the last Section is the conclusion of the study.

2 BLUR DETECTION TECHNIQUES

Blur detection is one of the interesting research areas in computer vision and image processing like in (Cruz-Roa et al, 2013; Yang, Zhou and Bai, 2013; Fang, Tao and Jia-Lin, 2017), and (Ancheta et al, 2018). Most of the captured images usually contain two types of regions: blurred and sharp. Blur can be categorized into two types: a) defocus blur or also known as out-of-focus blur, which is caused by the visual imaging system and b) motion blur or also known as camera-shake blur, which is caused by the relative motion between camera and scene objects (Ali and Mahmood, 2018).

Study (Pertuz et al, 2013), reviews 36 different techniques or focus measure operators to compute the blurriness metric of an image, some of them are simple and straight forward using just grayscale pixel intensity statistics, other are more advanced and feature-based that evaluate the local binary patterns of an image.

A total of 32 different blur measure operators was reviews for single image blur segmentation in (Ali and Mahmood, 2018). Some number of measure operators reviews included are originally developed for autofocus and shape from focus (SFF) techniques by (Abdel-Qader et al, 2003).

While in (Bansal et al, 2017), reviews 3 different blur detection techniques such as laplacian operator, fast fourier transform, and haar wavelet transform. In their study, Laplacian operator was selected for testing and successfully identify if the image is blurred or sharp.

In other literature, Tenengrad technique is used to extract the degradation degree of each target part in the image. Tenengrad technique was used in (Gao, Han, and Cheng, 2018) as operator used to evaluate the iris image's definition.

With the help of the related research papers available in public domain, conducting about blur detection techniques, we consider some related image blur detection techniques in our study and test the performance of each technique.

There are many image blur detection techniques to detect whether an image is blurred or sharp. Some of them are:

2.1 Fast Fourier Transform (FFT)

In Fourier transform, this method calculates the frequencies in the image at different points and based on the set level of frequencies it decides whether the image is blurred or sharp. When there is a low amount of frequency based on the set level of frequencies then it declares that the image is blurred otherwise, if the computed frequencies is high then the image is sharp. The decision that will be the value of low and high frequencies is based on the programmer. (Pertuz et al, 2013).

2.2 HaarWavelet Transform (HWT)

In this method, the images are split into NxN by iterating on each tile of the 2Dimensional HWT, and grouping diagonally, vertically, or horizontally connected tiles into clusters containing images are then declared blurred (Tong, Li, Zhang, and Zhang, 2004).

2.3 Laplacian Operator (LAP)

This method is implemented to discover edges in a picture. It is additionally a derivative operator but the basic contrast between different operators like Sobel, Kirsch and Laplacian operator is that all other derivatives are first order derivative mask. Laplacian operator is further separated into two classification which are the positive Laplacian operator and negative Laplacian operator.

2.4 Modified Laplacian (MLAP)

The modified laplacian is developed to compute local measures of the quality of image focus. By getting the absolute values of the second derivatives in x and y directions (Pech-Pacheco et al, 2000).

2.5 Tenengrad (TEN)

The well-celebrated focus measure based on image gradients obtained by the convolving the image with sobel operator that can also be considered as blur measure operator (Pech-Pacheco et al, 2000).

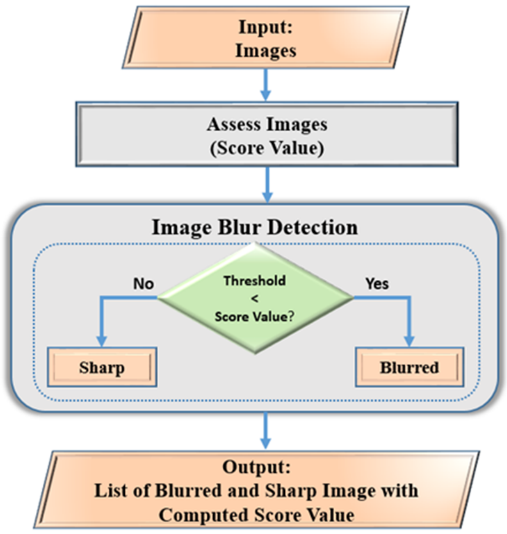

Figure 2: Flowchart of Image Blur Detection Techniques Processes.

Figure 2 shows the processes performed by the different blur detection techniques for testing. The user should input the value for threshold and Gaussian kernel for assessing and computing the score values of the inputted image. Based on the set threshold and Gaussian kernel, the calculated score value will be the basis of the image input is blurred or sharp.

3 EXPERIMENTAL METHODOLOGY

In this section, we describe the methodology we followed to perform a comparative analysis of image blur detection techniques. This study was programmed and tested in Python 3.6, using notebook computer, which has Intel Core i7-8750H CPU @ 2.20GHz and 8.0 GB RAM with the Windows 10, 64bit operating system.

3.1 Dataset

To quantitatively evaluate the performance of the different blur detection techniques, we randomly selected 200 blur and sharp images from the dataset provided in the study of [23]. The RGB image is 640 x 480 pixels. The blur images may have motion blur, out-of-focus blur, and synthetic blur.

Selecting proper threshold value totally depends on the domain. If the selected threshold is too high or too low then the images would be marked falsely, for example, if an image is sharp and the threshold is too high then the image will be marked blurry.

3.2 Evaluation Measures

Table 1 shows the confusion matrix model used to evaluate the accuracy of the different blur detection techniques.

Table 1: Confusion Matrix.

		Predicted Value	
		Negative (N)	***Positive (P)***
Actual Value	***Negative (N)***	True Negative (TN)	False Positive (FP)
	Positive (P)	False Negative (FN)	True Positive (TP)

where:

- Positive (P): Observation is positive (image is blurred)
- Negative (N): Observation is not positive (image is not blurred (sharp))
- True Positive (TP): Observation is positive, and is predicted to be positive (image is blurred and predicted as blurred)
- False Negative (FN): Observation is positive, but is predicted as negative (image is blurred and predicted as sharp)
- True Negative (TN): Observation is negative, and is predicted to be negative (image is sharp and is predicted to be sharp)
- False Positive (FP): Observation is negative, but is predicted positive (image is sharp, but is predicted as blurred)

This different blur detection techniques are also measure based on the following criteria:

1) Precision: a measure of relevance between the retrieved result and the observation. It refers to the fraction of the detected blurred (sharp) pixels which are actually blurred (sharp).

$$Precision,\ P = \frac{T_p}{T_p + F_p} \tag{24}$$

Where T_p means that the blurred (sharp) pixel has been correctly detected as blurred (sharp) pixel and F_p expresses that a pixel has been inaccurately detected as blurred (sharp) but it was sharp (blurred) actually.

2) Recall: also called as sensitivity in binary classification, it is a measure of the ability to retrieve the relevant results. It depicts the fraction of the actual blurred (sharp) pixels which are detected.

$$Recall,\ R = \frac{T_p}{T_p + F_n} \tag{25}$$

Where Fnnmeans that a pixel has been inaccurately detected as sharp (blurred) but it was blurred (sharp) actually.

3) F-measure: is a measure of a test's accuracy and is defined as the weighted harmonic mean (average) of the precision and recall of the test.

$$F\text{-}measure,\ F = 2\ x \frac{Precision\ x\ Recall}{Precision + Recall} \tag{26}$$

4) Accuracy: the ratio between the number of blurred (sharp) images correctly classified.

$$Accuracy,\ A = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{27}$$

5) Execution Time: total number of run-time during the execution of images

These quantitative measures provide an appropriate tool for analysis and evaluation of dataset.

4 RESULTS AND DISCUSSIONS

In this section, we discussed the results conducted during experimentation to be able to analyze the comparative performance of the different image blur detection techniques. Figure 3 shows a sample result of blur image after using blur detection techniques. While, figure 4 shows a sample result of sharp image after using blur detection techniques when evaluated and tested using Python 6.3. The Gaussian kernel of all techniques was set to three (3) and set the proper threshold value.

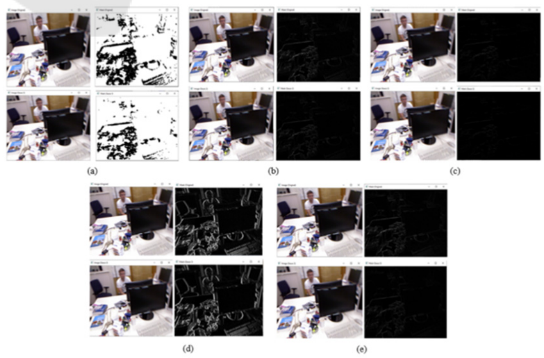

Figure 3: Result of BlurImages using Blur Detection Techniques; Result of (a) Fast Fourier Transform; (b) Laplacian Operator; (c) Modified Laplacian; (d)Tenengrad; and (e) HaarWavelett Transform.

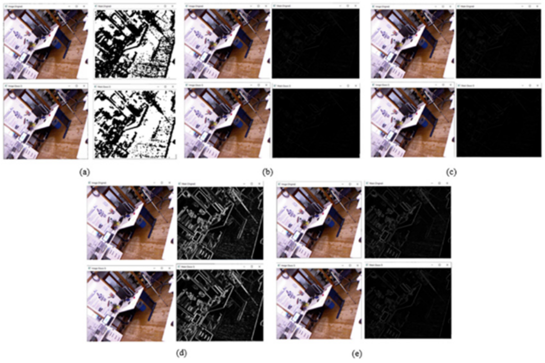

Figure 4 Result of Sharp Images using Blur Detection Techniques; Result of (a) Fast Fourier Transform; (b) Laplacian Operator; (c) Modified Laplacian; (d)Tenengrad; and (e) HaarWavelett Transform.

Table 2: This caption has one line so it is centered.

Blur Detection	**TN**	**FP**	**FN**	**TP**	**Accuracy (%)**	**Total Time (sec)**
FFT	100	0	13	87	93.5%	6.2001
LAP	73	27	2	98	85.5%	1.1482
MLAP	95	5	27	73	84%	0.8951
TEN	94	6	6	94	94%	5.6921
HWT	99	1	5	95	97%	6.0370

Table 2 shows the confusion matrix results of the performance comparison of different blur detection techniques. Provided the assessment results, in terms of accuracy rate, HWT leads the best results follows by TEN, FFT, LAP, and MLAP sequentially. In terms of execution time, MLAP leads the best results follows by LAP, TEN, HWT, and FFT sequentially.

Table 3: Comparison of Blur Detection Techniques.

Blur Detection	**Precision Score (%)**	**Recall Score (%)**	**F-Measure Score (%)**	**Total Time (sec)**
FFT	1.0	0.87	0.93048	6.2001
LAP	0.784	0.98	0.87111	1.1482
MLAP	0.9358	0.73	0.82022	0.8951
TEN	0.94	0.94	0.94	5.6921
HWT	0.9895	0.95	0.96938	6.0370

Table 3 shows the summary results of the performance comparison of different blur detection techniques. Provided the assessment results to measure the scores are the precision score, recall score, and F-measure score. Also, we considered the total processing time (execution time) of each technique. FFT got the highest precision score, while LAP got the highest recall score, and HWT got the highest f-measure score. In terms of execution time, MLAP performs the fastest processing time.

5 CONCLUSIONS

The study aims to conduct comparative analysis about the different image blur detection techniques. Based on the results, in terms of accuracy rate, HWT leads the best result. Based on the computed scores, FFT got the highest precision score, while LAP got the highest recall score, and HWT got the highest f-measure score. In terms of execution time, MLAP performs the fastest processing time among them all.

The next stage, as part of our long term project goal, we planned to conduct a comparative analysis of the different image restoration or deblurring techniques that can be used in our long term goal.

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