Pre-processing Techniques for Detection of Blurred Images

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Pre-processing Techniques for Detection of Blurred Images

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Abstract Blur detection and estimation have progressively became an imminent arena of computer vision. Along with heightening usage of mobiles and photographs, detecting the blur is purposed over to enhance or to remove the images. PrE-processing Techniques for DEtection of Blurred Images(PET-DEBI) was framed to detect the blurred and undistorted images. The frailty of Laplacian has been overcome by Gaussian filter to remove the noise of the image; then, the variance of Laplacian is calculated over the images. Through analysing the variance of the images, appropriate threshold is circumscribed and further used as limitation to define blurred and unblurred images. PET-DEBI was implemented and experimented yielding encouraging results with accuracy of 87.57%, precision of 88.88%, recall of 86.96% and F-measure of 87.91%.

Keywords Blur detection · Blur estimation · Gaussian Filter · Laplacian function · Threshold fixing

1 Introduction

Blur detection and estimation assist the field of computer vision with auto-focussing technique and quality assessment of the image. The incremented availability of good mobiles at affordable rate has benefited the people to capture increased number of digital images and to store them [6]. This has unlocked the field of blur detection, blur estimation and de-blurring of the images. Blur is defined as the phase of image where its content turns out to be difficult to read and understand. The image may become blur owing to limited contrast, untimely exposure, improper lighting environment

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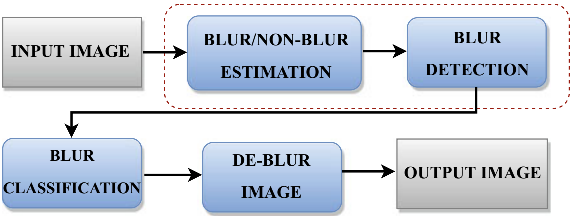

Fig. 1 Stages of blur detection framework

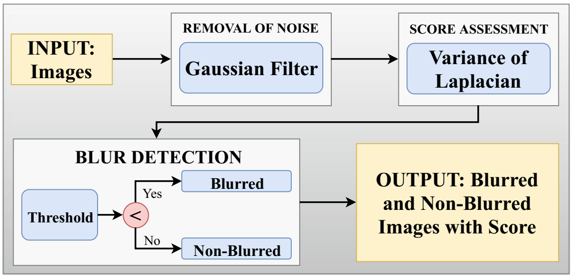

Fig. 2 Architecture of PET-DEBI

and indecorous device handling. The commoners have a trend of capturing hundreds of images daily, and it will be highly useful if a technique is skilled with automatic detection of blurred images and its deletion which will avoid the time of glancing through all the images and deleting it one by one [3]. At the same time, it will succour in increased space for the storage of images. Multitudinous accusations [10] arise from the fields like remote sensing, medical imaging, microscopy, visually impaired users and astronomy where blurred images bring about predicament in the diagnostics [4] (Fig. 1).

Figure 2 reveals the stages of the blur detection framework. The proposed work concentrates only on the stages which comprise blur/non-blur estimation and blur detection which is enclosed in red-dotted lines in Fig. 2. The proposed work, PrE-processing Techniques for DEtection of Blurred Images(PET-DEBI), was aimed as the pre-processing step in the text recognition from natural scene images, wherein there is the need to remove the blurred images in the first stage before processing into the phases of segmentation and recognition of text.

The proposed work contributes:

– To remove the noise of the image which may hinder the process of blur detection.
– To identify the optimal threshold value which forms the basis of the blur detection.
– To classify the images into blurred (B) and not blurred (NB) images based on the identified threshold value.

Section 2 lists some of the works associated in the field of blur detection, followed by the details of the proposed work in Sect. 3. Section 4 contains the experimentation and result analysis; finally, the conclusion and future enhancements are furnished in Sect. 5.

2 Related Works

Bolan Su et al. state various kinds of blur, notably motion blur, defocus blur and blend blur [7]. At the time of exposure, if there exists any relative motion between the camera and the object, then it is defined as motion blur. If the object is out of focus at the time of exposure, then its called as defocus blur. At the time of exposure, if there exists motion between the camera and object as well as the object is out of focus, then those types of blurs are named as blend blur. The stage blur detection detects the presence of blur in the image, blur estimation detects the measure of blur in the image, blur classification identifies the type of blur, and finally, the de-blur removes the blur from the image and gives the refined form of the image. PET-DEBI considers all the blur types as a single domain and detects the image if blurred stating the measure of blurriness in the image.

Dong Yang et al. [11] had made an attempt to identify the blurred regions of the image using total variation approach and had estimated the blur kernel conclusively restored the blurred region, he had simulated the experiment and had produced the results. Blur detection task is performed by Rui Huang et al. through convolutional neural networks (CNNs) [1]. The drawback with this model is that the data hungry CNN model requires a vast amount of data for training purpose, which becomes a real-time conundrum. Another research [8] performs a binary classification of blur detection into blurred and non-blurred images using Haar wavelet transform; they have used edge detection technique to identify the blurriness in the image. They also claim that their approach is 50% faster than their previous approaches.

Till Sieberth et al. proposed saturation image edge difference standard deviation (SIEDS) to detect and eliminate blurred images in order to assist the unmanned aerial vehicles (UAVs). Like human, the proposed method compares the images with other images and surmises a conclusion for the utilization of the image [5]. Van Cuong et al. proposed a fuzzy model to accomplish blur estimation on document images. The blur score is determined by the average of all the pixels in the blurred region and had evaluated on two real-time databases [2]. Through the current state of the arts, the importance of blur detection in the field of computer vision has been revealed and the various noteworthy benefits in the diversified real-time solicitations.

3 Proposed Work

The proposed work takes in images as input, and as the PET-DEBI uses Laplacian operator to determine the score of blurriness, it becomes mandatory to remove the noise of the image, as Laplacian is very sensitive to noise. The noise of the image is removed by Gaussian filter and further provided to the next module, where the variance of Laplacian operator is calculated and the resulting score is used to detect the blurred images. If the calculated score is less than the measured threshold, then it is blurred, otherwise non-blurred. Finally, output is the images that are classified into blurred and non-blurred with calculated score, which acts as aid to eliminate the blurred images.

3.1 Gaussian Filter

Gaussian filter exerts Gaussian function to remove the noise of the image. Laplacian operator is known for its sensitivity to noise which will hinder its performance, so it becomes compulsory to eliminate the noise. The Gaussian function produces a filter that can be applied to each pixel in the image. It is calculated for two dimensions as follows:

$$GF(\alpha, \beta) = \frac{1}{(2\pi\sigma^2)} \mathrm{e}^{-\frac{(\alpha^2+\beta^2)}{2\sigma^2}} \tag{1}$$

where α is the measure between the origin and horizontal axis, and β is the measure between origin and vertical axis. σ is the Gaussian distribution standard deviation.

3.2 Variance of Laplacian

Laplacian operator is the second-order differential operator in n-dimensional Euclidean space. It is expressed as the divergence (∇) of the gradient (∇f). The Laplacian of f is the sum of the second partial derivatives in the Cartesian coordinates x_i which is defined as follows:

$$\nabla^2 f = \sum_{i=1}^{n} \frac{\partial^2 f}{\partial x_i^2} \tag{2}$$

Then -DEBI performs the variance over the resultant. The Laplacian emphasizes the regions with rapid change in intensity. It is known fact that images with very less edges are assumed to blurred images. The high variance discloses that there are more edge-like and non-edge-like objects recording high response, whereas the low variance discloses that there is little edges recording tiny spread of responses.

3.3 Threshold Computation

If the calculated variance is below the threshold, then it is concluded as “blurry”; otherwise, its “not blurry” (undistorted). The complication is setting the correct threshold as too low threshold for blur detection can erroneously mark blurry as not blurry images and too high threshold can erroneously leave the blurry images out. So the PET-DEBI has formulated out to find the proper threshold. PET-DEBI ran over the 2450 images containing undistorted and blurred images. And the variance of Laplacian for each image is measured. Then, the average of the variance of the undistorted as well as blurred images is estimated to form the near accurate threshold.

$$\frac{1}{(n+m)}\left(\sum_{i=1}^{n}\nabla^2 f(\omega)+\sum_{j=1}^{m}\nabla^2 f(\psi)\right) \tag{3}$$

where n and m mention the number of undistorted and blurred images, respectively, ω and ψ represent the set of undistorted and blurred images, and $\nabla^2 f$ specifies the variance of Laplacian.

4 Experimentation and Result Analysis

The PET-DEBI was programmed in Python, in Ubuntu distribution of Linux operating system.

CERTH dataset is functioned to perform image quality assessment, which contains 2480 digital images containing 1249 undistorted images and 1231 natural and artificial blurred images. The threshold is fixed over the training dataset and evaluated over the testing set of CERTH dataset. Along with the CERTH dataset, PET-DEBI is tested over the collection of random 2200 sample images taken from the Google.

Table 1 and Fig. 6 list out the comparison of blur detection of PET-DEBI with other such works and have given promising results with accuracy of 87.57%, precision of 88.88%, recall of 86.96% and F-measure of 87.91%. It was able to detect blurred images in five to seven microseconds.

Table 1 Comparison of blur detection methods over CERTH

Method	Accuracy(%)	Precision(%)	Recall(%)	F-Measure(%)
Giang Sontran et al. [8]	75.34	77.27	74.56	75.89
Seyfollah Soleimani et al. [6]	62.86	70.01	66.66	68.29
Siddartha Pendyala et al. [3]	81.14	88.57	71.26	78.98
Bryan M Williams et al. [9]	84.21	85.36	79.55	82.35
PET-DEBI	87.57	88.88	86.96	87.91

Fig. 3 CERTH dataset—blurred estimation score

Fig. 4 CERTH dataset—not blurred estimation score

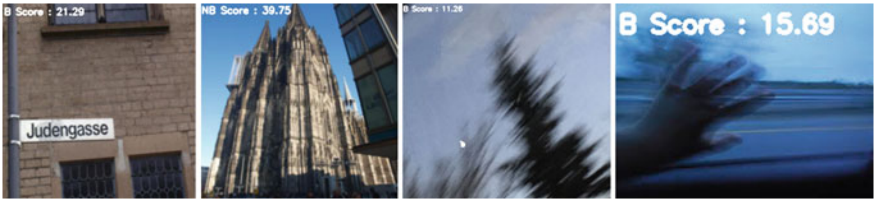

Fig. 5 CERTH dataset—incorrect estimations and random images from Google—Blurred and Non-blurred estimation score

Figure 3 is the samples of estimation of blurred images, and Fig. 4 is the samples of the estimation of clear images. In Fig. 5, the first two images show the incorrect estimations of the PET-DEBI and last two images show random estimation of the proposed work over Google images.

5 Conclusion and Future Enhancements

PET-DEBI is contrived to detect the blurred images. In order to overcome the sensitivity of Laplacian towards noise, Gaussian filter was employed over the images to remove the noise, and the variance of Laplacian was calculated over the images. If the variance is lesser than the computed threshold, then it is termed as blurred images; otherwise, they are undistorted images. PET-DEBI produced better results compared to its other works with lesser amount of time for detection. Further, the work can be extended to de-blur the images and enhance it (Fig. 6).

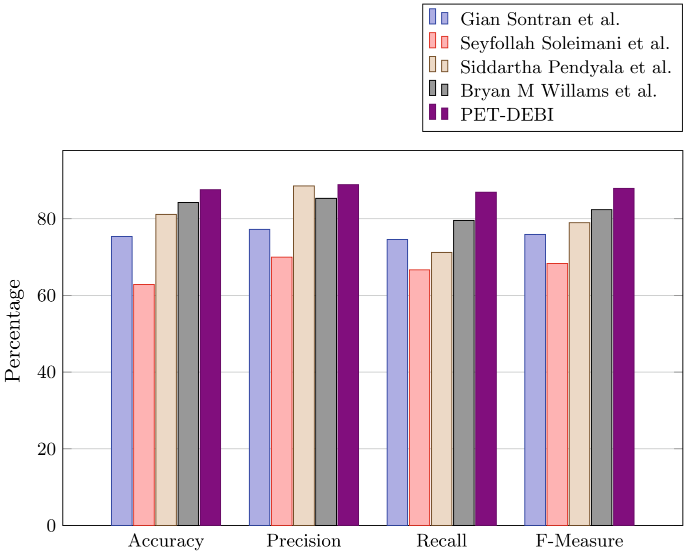

Fig. 6 Comparison over CERTH

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