

RANDOM FOREST CLASSIFIER APPROACH FOR BLURRED IMAGES

Maganti Syamala¹, N.J.Nalini², R.Ragupathy³,
lakshmana phaneendra Magalur⁴, J. Amudhavel⁵
^{1,2} Department of Computer Science and Engineering
Annamalai University, Annamalai Nagar,
Chidambaram, Tamilnadu-608002
³Dhanekula Institute of Engineering & Technology
Ganguru, Andhra Pradesh 521139
^{4,5}K L University-Green Fields,
Vaddeswaram, Guntur, Andhra Pradesh-522502

Abstract: Image blurring is a serious issue leading to degradation of image and thereby loss of information. An image is blurred due to the object, defocusing of the lens, atmospheric turbulence, etc. Images can be restored if information about the original image or the blur is known. Degradation due to defocus blur is considered in this paper. The estimation of defocus blur radius is treated as a classification problem here. A technique to classify the blur radius using random forest classifier is proposed in this paper. Third and fourth statistical moments, calculated on the spectrum of the blurred image, are used as features for classification in the proposed method. The proposed technique is applied on images from the USC-SIPI Image database. The experiment results display defocus radius classification accuracy of 94.37%. The selection of skewness and kurtosis as handcrafted features for the defocused blur image and usage of random forest classifier for defocus radius classification has been approached for the first time in such a problem. The choice of features adds to the novelty and the efficiency of this approach.

Keywords: defocus blur; image blurring; parameter estimation; point spread function; random forest

I. Introduction

In the Internet era, restoration of blurred images is a bottleneck problem to deal with real-world applications. Images can be blurred or degraded due to atmospheric turbulence, capturing mechanism of sensor. In majority of the situations, the information about the original image or the blurring functions are not known. Hence, restoring the image or extracting information from the blurred image

becomes a tedious task. Restoration of images, when the blurring function and the original image are unknown, is called blind image restoration [1]. This paper deals with estimating the parameter of images degraded by defocus blur. Once the radius of defocus can be determined, the image can be restored by any classical image restoration algorithm.

Much work in literature has been done on estimating the defocus blur radius in the frequency domain by exploiting the spectral zeros. The extent and type of blur can be determined from the frequency response of PSF by exploring the periodic zero crossings, as given by [2] and [3], which gave the mathematical modelling of those zero crossings. The blur radius was estimated by applying polar transformation of the defocus image in the frequency domain in [4]. Neural networks individually and in combination with other filters were trained and employed for estimation of radius of defocus. Chen et al. [5] estimated the radius in the frequency domain. Restoration of images was done with the obtained PSF using the trained neural network. RBF networks were used in combination with Wiener and Kalman filter for estimation and restoration. In [6], defocus blur radius is estimated in wavelet domain by using a RBF network and iterative Wiener filtering is used for restoration. While a RBF NN along with Kalman filter were used to estimate defocus blur parameter and then restoration. The RBF was trained in wavelet domain and then Kalman filter was used for restoration. RBF network in a cellular neural network was used to estimate the defocus blur parameter in wavelet domain by [8], which provides robustness against noise. A General regression neural network

(GRNN) is trained and used for estimation of blur parameters in [9]. Natural image patches are taken as input, which is pre-processed to extract frequency domain features before training a DNN. Though these architectures provide noise robustness or better classification accuracy, the structures of neural networks are complex and computationally extensive.

This paper proposes a method to classify the defocus blur radius by using Random Forest classifier, which does not require the complete image or image patches as an input for training. The random forest classifier is trained by statistical features extracted from the log of blurred image. Edge detection is applied to the log of Fourier transform of the input blurred image and third and fourth statistical moments – skewness and kurtosis values are calculated on it. These values are input as features to train the random forest classifier and the defocus radius as its corresponding class output.

The upcoming sections in this paper is organized as follows: Section II introduces the image degradation system and defines the defocus PSF. The proposed technique to classify the blur radius using random forest classifier is discussed in Section III. It also describes the procedure to extract the features to train the random forest classifier. Section IV gives the experimental results and section V discusses the conclusion.

II. Background Theory

In the image degradation model, blurring an image is equivalent to convolving the clean image with the blur kernel. Any noise is modelled as additive. The following equation mathematically formulates the blur model.

$$g(x, y) = f(x, y) * h(x, y) + n(x, y) \quad (1)$$

Here, $n(x, y)$ is the additive noise, $h(x, y)$ represents the PSF, $f(x, y)$ is the original image and $g(x, y)$ is the blurred image.

Applying Fourier transform on both sides of the equation,

$$G(u, v) = F(u, v)H(u, v) + N(u, v) \quad (2)$$

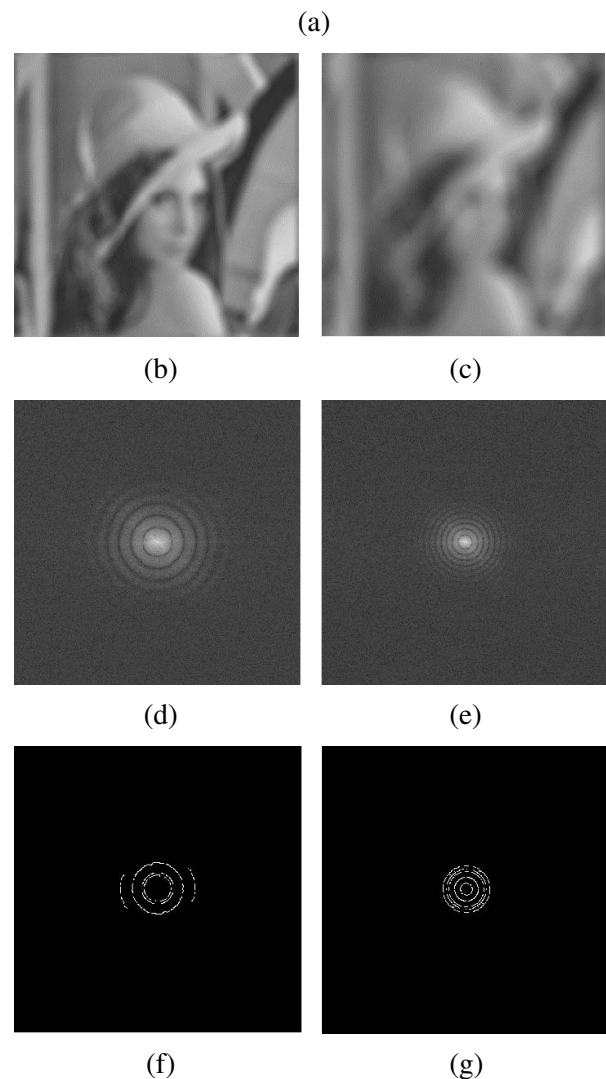


Figure 1. (a) Original image; (b) blurred with defocus or radius 12; (c) blurred with defocus of radius 25; (d) and (e) Fourier transform of (b) and (c) respectively; (f) and (g) output of edge detection applied to the (d) and (e)

$G(u, v)$, $F(u, v)$, $H(u, v)$ and $N(u, v)$ represent the discrete Fourier transform of the spatial domain functions $g(x, y)$, $f(x, y)$, $h(x, y)$ and $n(x, y)$ respectively. From (2) one sees that in cases where the additive noise can be neglected due to low magnitude, the regions of zero crossings in $F(u, v)$ and $H(u, v)$ form zeros of $G(u, v)$. Hence the parametric expressions representing the degradation functions can be obtained by exploring the spectral zero crossings of degraded image. So,

the frequency spectrum of the blurred image needs to be analyzed.

This paper considers classification of blur parameter in images degraded by defocus blur. Defocus occurs when some part of the scene are in focus and others are not. It mainly depends on the distance between the camera and the object, the focal length and the aperture of the lens. The point spread function (PSF) or blur kernel of defocus blur can be expressed as:

$$h(x,y)=\begin{cases} \frac{1}{\pi R} & \text{if } \sqrt{x^2 + y^2} \leq R \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where, R is the defocus blur radius, and is proportional to defocusing extent. Fig. 1 shows input image blurred with defocus of radius 12 and 25. The Fourier transform of (3) is:

$$H(u,v)=\frac{J_1(\pi R r)}{\pi R r} \quad (4)$$

has circular symmetry, the frequency spectrum of every defocus blurred image can be characterized by periodic occurrence of concentric circular dark rings, as shown in Fig. 1 (d) and (e). As the blur radius increases, the size of the concentric circles in the frequency spectrum of the blurred image decreases. This is also evident from Fig.1.

Considering r_0 as the radius of the first zero crossing or as radius of the innermost dark circular ring in the frequency spectrum $G(u, v)$ of the defocus blurred image, the following relationship [3] has been derived between r_0 and R (defocus blur radius):

$$R=\frac{3.83L_0}{2\pi r_0} \quad (5)$$

where $L_0 \times L_0$ is the size of the DFT of the blurred image.

III. Proposed Method For Defocus Blur Parameter Estimation

The radius of blur is classified by using a random forest classifier. Random forests are one of the most widely used machine learning algorithms for classification. So far, this has been the first time that radius of defocus has been classified. The classifier is trained by extracting features from the spectrum of the blurred image.

A. Random Forest Classifier

In Random forest classifier Each decision tree is trained by using a randomly drawn subset of the training set. Each tree generates a vote (decision) on the given test input and the classified output is chosen as the class which has received maximum votes. Fig. 2 shows random forest classifier having n decision trees. Each tree is grown as follows:

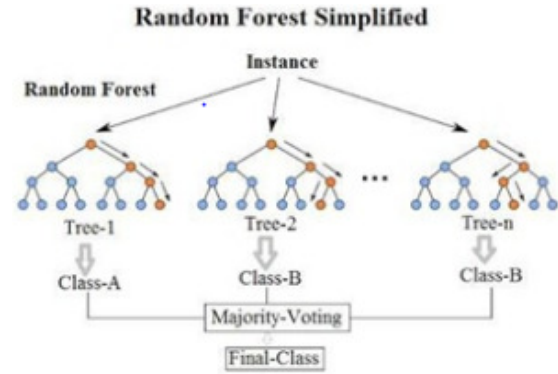


Figure 2. Example of Random Forest Classifier

In this paper, the random forest classifier is trained by input vectors which are statistical features calculated by on the edge detected output of the log of Fourier spectrum of the blurred image.

B. Blur Features

As discussed in section 2, the spectrum of defocused blurred image exhibits concentric circles, whose radius is related to the radius of the blur. The random forest classifier is trained by extracting features from this spectrum. For extraction of features, the input blurred image is pre-processed considering the image. The log of the magnitude of this Fourier spectrum is considered, which displays concentric rings distinctly. Canny edge detection is employed on this spectrum, such that the concentric rings are visible and result into a continuous outline of the ring. The innermost circle of these concentric rings, which relates to the radius of the blur, given by (5) is extracted by using the First white method of [10]. The remaining portion of the spectrum is masked off. Hand-crafted features are then extracted from this ring in the spectrum. This process is depicted in Fig. 3.

Skewness is the indication of asymmetry of data and is expressed as:

$$g = \sum_{i=1}^n \frac{(x_i - x_j)^3}{\sigma^3} \quad (6)$$

And kurtosis is an indication of pointedness of the data, expressed as

$$k = \sum_{i=1}^n \frac{(x_i - x_j)^4}{\sigma^4} \quad (7)$$

where σ is the variance.

It is evident from (5) that the radius of the innermost circle in the spectrum of the defocused blur image is inversely proportional to the blur radius. Hence, the skewness and kurtosis values calculated on this ring in the spectrum are distinct values with respect to the blur radius. A combination of these third and fourth moments is taken as features of the defocused blur image and are considered as training and testing inputs of the classifier

C. Training the Random Forest Classifier

To train and test the random forest classifier, blur features - skewness and kurtosis are calculated on the edge detected output of the log of the Fourier spectrum. The random forest classifier is constructed of 10 trees and is trained by vector inputs of these skewness and kurtosis values with the known blur radius as the class label. From the total samples, $3/4^{\text{th}}$ of the portion are used for testing the classifier.

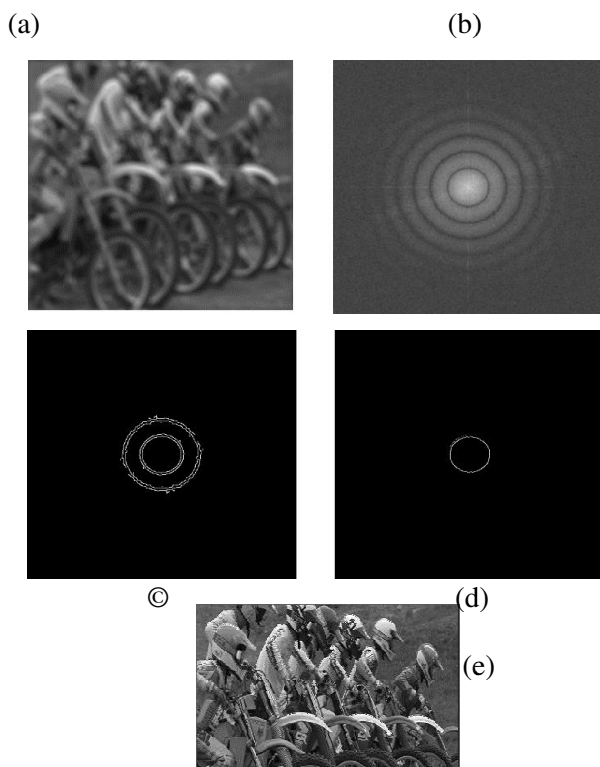


Figure 3. (a) Inputted image [12]; (b) defocus blur of radius 8; (c) Frequency spectrum of (b); (d) Output of Canny edge detector applied in (c); (e) Detecting the innermost circle and masking the rest of the spectrum

IV. Experimental Results

We considered the USC-SIPI dataset [11] for experimentation. From this dataset, 100 images are blurred by defocus blur having 8 different defocus blur parameters, generating 800 defocused blurred images in total. The blur radius used for generating this dataset are 5, 8, 10, 12, 15, 20, 23 and 25. Each blur radius is treated as a class and each of the 100 images generated by a blur radius are assigned a class label, thus giving 8 class labels for 8 different defocus blur radii. Skewness and kurtosis values are extracted from each image in every class by the proposed method. From each class, the extracted features from 80 images are randomly selected training and from 20 images for testing. Thus, features from 640 images collectively are used to train the random forest classifier. The features calculated on the remaining 160 images are taken to test the classifier. The pre-processing and generation of random forest classifier is implemented in MATLAB. The random forest is constructed having 10 trees to classify the defocus radius of the test set based on the training dataset.

Table I. Confusion Matrix For Classification Of Defocus

	5	10	12	15	20	23	25
5	20	0	0	0	0	0	0
8	2	0	0	0	0	0	0
10	0	20	0	0	0	0	0
12	0	0	19	1	0	0	0
15	0	0	0	20	0	0	0
20	0	0	0	0	20	0	0
23	0	0	0	0	2	14	4
25	0	0	0	0	0	1	19

The confusion matrix of the classification is shown in table.

The classification accuracy on this dataset came out to be 94.37%, which is appreciably higher. It is also evident from the table that misclassification occurred majorly at higher blur radius, where the spectrum radius greatly decreases. Once, the blur radius is estimated, the defocus PSF can be

generated and this can be employed by any non-blind image restoration algorithm to restore the blurred image.

V. Conclusion

A method to estimate the defocus blur radius using Random Forest classifier has been proposed in this paper. Skewness and kurtosis, which are third and fourth statistical moments are considered as features for training the classifier. The combination of these handcrafted features for discriminating the defocus radius and using random forest classifier has so far never been undertaken for the problem of defocus blur parameter estimation. The radius classification results exhibit higher amount of accuracy, thus validating the efficiency of the proposed method and the choice of skewness and kurtosis as features distinctly describing the blur radius for classification.

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