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## Review on Estimation of Defocus Map using LBP based Segmentation

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**ABSTRACT:** Defocus obscure is to a great degree basic in pictures caught utilizing optical imaging frameworks. It might be unwanted, yet may likewise be a deliberate masterful impact, in this way it can either upgrade or hinder our visual impression of the picture scene. For assignments, for example, picture rebuilding and protest acknowledgment, one might need to fragment an incompletely obscured picture into obscured and non-obscured locales. In this paper, the investigation of sharpness metric in light of nearby twofold examples and a vigorous division calculation to isolate all through concentration picture districts. The sharpness metric adventures the perception that most neighborhood picture fixes in foggy areas have altogether less of certain nearby parallel examples contrasted and those in sharp districts. Utilizing this metric together with picture tangling and multiscale derivation, we got amazing sharpness maps. Tests on many incompletely obscured pictures were utilized to assess our obscure division calculation and six comparator techniques. The outcomes demonstrate that our calculation accomplishes near division comes about with the cutting edge and have huge speed advantage over the others in additionally work.

**KEYWORDS:** Defocusmap, Defocus Blur, Segmentation, LBP Technique

### I. INTRODUCTION

FOCUS blur in an image is the result of an out-of-focus optical imaging system. In the image formation process, light radiating from points on the focus plane are mapped to a point in the sensor, but light from a point outside the focus plane lights up a non-point district on the sensor known as a hover of perplexity. Defocus obscure happens when this circle turns out to be sufficiently expansive to be seen by human eyes. In advanced photography, defocuses obscure is utilized to obscure foundation and "fly out" the primary subject utilizing vast gap focal points.

Be that as it may, this restrains computational picture understanding since obscuring of the foundation stifles subtle elements gainful to scene translation. For this situation, partition of the obscured and sharp districts of a picture might be important so post-preparing or reclamation calculations can be connected without influencing the sharp areas, or so picture highlights are just removed from in-center locales. Defocus estimation plays a vital role in the field of image processing and computer vision and it finds a broadrange of application such as video processing, depth and scale estimation, medicalfield, image visualization and imagesharpening. In the image processing blur arises due to various factors - uniform motion blur due to camera shake(it degrades sharpness and some time produces ghostly secondary images within the original image), non uniform motion blur caused due to object movement(result in blurred object image and blurred background), defocus blur(in which only main object will be in focus and background will be blurry in image) and spatially varying blur caused due to atmospheric turbulence (it prevents us from seeing as far away the views of ground based telescope as would be theoretically possible). Now, Aperture is significant in photography because aperture either adds a dimension by blurring the surroundings or automatically it brings everything in focus. In optics aperture is a hole or opening within the lens through which light travels to the camera sensors (If aperture is narrow then highly collimated beams are allowed resulting in a sharp focus at the image plane. If aperture is wide then uncollimated beams are allowed resulting in image that is sharp around where the lens is focusing). Now, depth of field is another word which is directly linked with size of aperture. Depth of field is defined as the region of acceptable

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sharpness in front of and behind the subject on which the lens is focused. The lower the f/stop the larger the opening in the lens (that is the maximum aperture) corresponds less depth of field and hence blurred background. In Fig (1) an example is shown in which image describes defocus present in background and focused object.

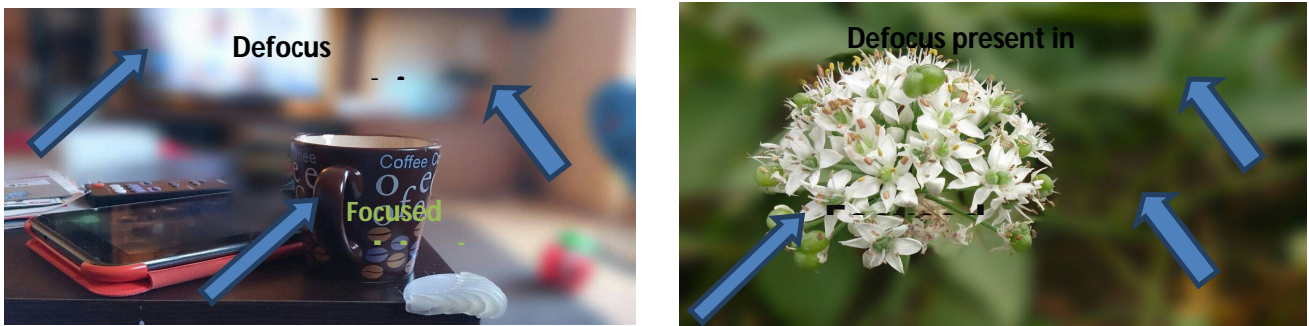


Figure 1: Example showing defocus blur present in background

The 2D map for an image of the scale parameter is entitled as defocus blur map, which indicates the point of local blur at each pixel in image. Edge detection is performed in defocus estimation; edges in images are the areas with strong intensity contrasts. Gradient methods detect edges by looking for maximum and minimum in the first and second derivative of image (image gradient is a directional change in intensity). In this paper our proposed method also estimates defocus by first taking image derivative and further blurring kernel is chosen which helps in this method to model blur map. Optical imaging system is shallow depth of field due to which images are captured with sharp foreground (object present in image is focused) but blurred background (surroundings).

## II. DEFOCUS BLURRING CONCEPT

As far as possible there are many methods for magnifying the defocus blur which is typically present in photographs. In this paper we introduced an effective method for defocus magnification. The magnified defocus blur present in background of images. By magnifying defocus we can conclude that output image looks more sharp as compared to original image which suffers from defocus blur and our method gives good result as compared to other existing methods.

Firstly we will define the radius of blurring kernel by which blurring can be performed in the whole image. So, we define radius of blurring kernel given as:

$$\text{int}[r] = \text{Max}_{W_m} \frac{[dA]}{W_m} \quad (1)$$

Where,  $dA$  is the 1<sup>st</sup> derivative of image function. And  $W_m$  is mean of kernel which is given as;

$$W_m = \frac{1}{I \times J} \sum_{i,j} W_{i,j} \text{ and } i, j = 0, 1, \dots, I, J \quad (2)$$

$$I = J = \text{int}[r]$$

And  $I$  &  $J$  are the window size dimensions. The blurring kernel radius value will decide the amount of blurring. Now, to get the result from the above concept we are performing convolution. So,

$$\text{Blurred image} = dA \otimes [W]_{r \times r} \quad (3)$$

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From the above result we get the image in which blurring is performed according to radius of blurring kernel and by which defocus present in image is blurred more and our main focused object looks much more sharp. Then thresholding is performed which determines the pixels which should be discarded and also those pixels which should be retained in our image. The Otsu's method search for the threshold that minimizes the intra-class variance that signifies that the variance within the class which is defined as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \quad (4)$$

Where weight  $w_i$  are the probabilities of the two classes divided by a threshold  $t$  and  $\sigma_i^2$  variances of these classes. At last the localization is done which gives the exact blur map. After the localization we get the blur map for gray image as well as color image and map for defocus magnification.

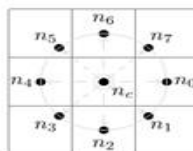


Fig. 4. 8-bit LBP with  $P = 8, R = 1$ .

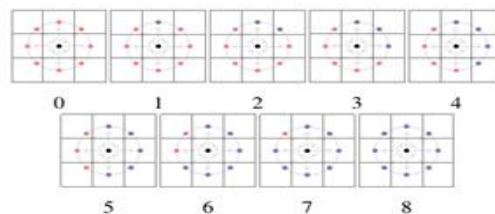


Figure 2: Defocus Blurring Concept

Important image features can be extracted from the image edges. Extracted features are employed for higher level computer vision algorithms (recognition). Before obtaining the blur map we first employ Gaussian filter to reduce the noise effect this operation in general termed as smoothing. The filtering is useful for noise reduction (side effect blurring). After the smoothing operation the noise is suppressed as much as possible and hence demarcation is done on the outcome of Gaussian filter for enhancing the quality of map. After Gaussian smoothing thresholding is performed this decides the pixels which should be discarded and also those pixels which should be retained from the image. As a last step localization is performed this gives the exact blur map (exact edge location).

For removing high frequency noise a Gaussian filter with small kernel is applied to the original image so it will remove high-frequency noise and suppress the blur caused by blur texture.

The Gaussian distribution in 1-D has the form:

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (5)$$

Where  $\sigma$  is the standard deviation of the distribution which controls the smoothing. We have assumed that the distribution has mean of zero (*i.e.* it is centered on the line  $x=0$ ).

In 2-D, anisotropic (*i.e.* circularly symmetric) Gaussian distribution is having the form:

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$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (6)$$

Once a suitable kernel has been designed, then the Gaussian smoothing can be accomplished by using standard convolution methods. The convolution is accomplished fairly rapidly since the equation for the 2-D isotropic Gaussian shown above is detachable into  $x$  and  $y$  components. Thus the 2-D convolution can be obtained by convolving with a 1-D Gaussian function in the  $x$  direction, and then convolving again with one 1-D Gaussian in the  $y$  direction. After the Gaussian smoothing enhancement is done for enhancing the result obtained from Gaussian filtering that means sharpening is done by means of demarcation. Demarcation measures the rate of change of a function and demarcation is done on the outcome of Gaussian filter for enhancement the quality of map.

The formula for the 1<sup>st</sup> derivative of a function is as follows:

$$dA = \sum_i (A_{i+1} - A_i) / (x_{i+1} - x_i) \quad (3)$$

Where  $A_i$  represents the pixel value.

At the end of this we will get the image in which it is shown that the high contrast region are mainly focused and out of focus region is having low contrast so it is demarcated .

### III. RELATED WORK

**Xin Yi et al. [1]**, proposed that camera shake during exposure may cause objectionable blur in images and damage photographs. Defocus blur is extremely common in images captured using optical imaging systems. It may be undesirable, but may also be an intentional artistic effect, thus it can either enhance or inhibit our visual perception of the image scene. For tasks, such as image restoration and object recognition, one might want to segment a partially blurred image into blurred and non-blurred regions. In this paper, we propose sharpness metric based on local binary patterns and a robust segmentation algorithm to separate in- and out-of-focus image regions. The proposed sharpness metric exploits the observation that most local image patches in blurry regions have significantly fewer of certain local binary patterns compared with those in sharp regions. Using this metric together with image matting and multiscale inference, we obtained high-quality sharpness maps. Tests on hundreds of partially blurred images were used to evaluate our blur segmentation algorithm and six comparator methods.

The results show that our algorithm achieves comparative segmentation results with the state of the art and have big speed advantage over the others.

**J. Shi et al. [2]**, proposed an edge detection technique in which edge detection is performed according to the first- and second-order derivatives of the input photograph. They used the Gaussian basic filter which calculate the center line of edges and respective blur response, their method perform edge detection using local scale control and their result gives only sparse defocus map (in which high contrast edges are highlighted). There are two approaches for edge detection search based and zero crossing.

**F. Couzinie-Devy et al. [3]**, further completed the work with an MRF and cross bilateral filtering which reduces the error during estimation. By using defocus interpolation method a full defocus map is obtained from the sparse map. Introduced method for defocus map generation in which defocus estimation is performed from the ratio obtained between the gradients of input and re-blurred images at edge locations, then obtained a full defocus map by propagating the blur quantity from edges to the entire image.

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**K. He et al. [4]**, technique model the blur map by applying local contrast prior which measured the defocus at each pixel and then MRF propagation used to refine the defocus map. The input picture is re-blurred by using a known Gaussian blur kernel and the ratio stuck between the gradients of input and re-blurred images is calculated. In this paper we have proposed a well-organized blur estimation method based on radius of blurring kernel and our proposed method is robust to noise and intrusion from neighboring edges. Without any revision to cameras or using additional illumination we can say that our method is able to obtain the good defocus map of an image captured by conventional camera.

**R. Fergus et al. [5]**, developed a method for restoring sharp image and produce blur map their method select best PSF. This technique requires specially designed aperture filter which heavily limits its domain of application. The recommended a method estimating the likelihood function of a given candidate (point spread function) PSF which is based on local frequency component analysis without deconvolution and this method is applied to detect motion blur but also applied for defocus blur identification. The introduced spectrum contrast approach for estimating defocus map from a single image. According to this approach blur affects the spectrum amplitude at the object edge only and edges contains the maximum information. This also takes contemplation in smoothness and color edge information to construct a coherent blur map that marks the amount of blur at each pixel. They have shown the comparison of various methods and different methods have been reviewed for estimation of defocus blur.

Table 1: Summary of Literature Review

Title	Methodology	Parameter	Scope
LBP-Based Segmentation of Defocus Blur	Sharpness metric based on local binary patterns and a robust segmentation algorithm	Average runtime = 27.75 sec, Precision = 0.85, recall = 0.82	Optical image system
Just noticeable defocus blur detection and estimation	Design defocus blur image using complex wavelet transform system	F-measure = 0.92, recall = 0.84	High-resolution imaging
Learning to estimate and remove non-uniform image blur	Design defocus blur image using singular value decomposition	Average runtime = 27.75 sec,	Digital Camera
A global sampling method for alpha matting	Sparse dictionary based on a large external set of defocus images	Sparsity Feature Value = 55, recall = 0.88	Digital photography
Design of Removing camera shake from a Single image	Edge width as a reference for depth measurement based defocus	Recall = 0.91, Precision = 0.91	Digital camera and optical system

The identified shadow elements are improved by intensity biased so as to maintain the intensity level of shadowed region equivalent to the non-shadow region. To do this process we have divided the whole shadow region into four parts and differently adjusted the intensity level to get high quality shadow removed image.

The simplest assumption that can be used to detect cast shadows is that regions under shadow become darker as they are blocked from the illumination source. Furthermore, since there is also ambient illumination, there is a limit on how much darker they can become. These assumptions can be used to predict the range of intensity reduction of a region under shadow, which is often used as a first stage to reject non-shadow regions. However, there are no methods which rely primarily on intensity information for discriminating between shadows and objects.

Here assumed the regions under shadow become darker but retain their chromaticity. Chromaticity is a measure of colour that is independent of intensity. For instance, after a green pixel is covered by shadow it becomes dark-green, which is darker than green but has the same chromaticity. This colour transition model where the intensity is reduced

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but the chromaticity remains the same is normally referred to as colour constancy [5]. Pixels in a shadow region usually have large hue value, low blue color value, and small difference between green and blue color values [6]. The detection stage in which shadow regions are detected, specifically by determining the shadow boundaries and the reconstruction stage in which the shadow is actually removed and a shadow-free image is produced

## IV. PROBLEM FORMULATION

The shadow removal problem can be broken down into two main constituent parts: shadow identification and shadow removal. Shadow identification is a well-defined concept, in which the presence of shadows upon different material image surfaces is detected and their exact position upon those surfaces is located. We primarily focus on shadow removal upon any one of these material surfaces. We assume that such an identification method has recognized a surface as having a shadow on it and passed it to our algorithm.

Our shadow removal approach is based on a simple shadow model where lighting consists of directed light and environment light. We try to identify how much direct light is occluded for each pixel in the image and relights the whole image using that information. First, we use a matting (extracting a foreground element from a background image by estimating an opacity for each pixel of the foreground element) technique to estimate a fractional shadow coefficient value. Then, we estimate the ratio of direct to environmental light, which together with the shadow coefficient, enables a shadow-free image to be recovered.

## V. CONCLUSIONS

In this paper, review is very simple yet effective sharpness metric for defocus blur segmentation. This metric is based on the distribution of uniform LBP patterns in blur and non-blur image regions. The direct use of the local raw sharpness measure can achieve comparative results to the state-of-the-art defocus segmentation method that based on sparse representation, which shows the potential of local based sharpness measures. By integrating the metric into a multiscale information propagation frame work, it can achieve comparative study with the state-of-the-art.

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