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Single Digital Image Multi-focusing Using Point to Point Blur Model Based Depth Estimation

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Abstract—The proposed paper focuses on Multi-focusing, a technique that restores all-focused images from defocused ones and generates images focused at different depths. The method proposed in the paper can be applied to images taken with an ordinary camera and does not require any specialized hardware. The method deviates from the existing de-convolution process for obtaining multi-focused images and highlights procuring a focused image by using only a single image. Blur map estimation is the core of the proposed method. Initially, a rough blur map is obtained which gives the blur amount at edge locations and by propagating the blur amount at edge locations to the entire image, the full blur map of the scene can be recovered. In order to produce photographs at different depths, a depth map is required. Since the amount of blur is proportional to the distance from the plane of focus, the blur map can be used as a cue for depth. The depth map is calculated using the blur map and the camera parameter information embedded in the defocused image. Using the depth map, multi-focused images can be obtained.

Index Terms— Multi-focusing, Depth estimation, blur estimation

I. INTRODUCTION

Multi-focusing, as the name suggests, is a technique that restores all-focused images from defocused ones and generates images focused at different depths. Limited focal length of optical lenses and non-optimal settings of cameras may result in defocus blur degradation of the captured image. In such cases, it is often required to remove the defocus blur and obtain a more focused image. Sometimes, the photographer intentionally wants to create defocus effects to give prominence to the main subject of the photograph or for other aesthetic reasons. This is easily achievable in professional cameras which are capable of obtaining shallow depth of fields and come equipped with manual focus. In conventional cameras, on the other hand, this is rather difficult. Multi-focusing proves useful in such situations. Such a technique is needed in more and more cases, such as low-end cameras, smart phone cameras and surveillance cameras.

Multi-focusing can be implemented using hardware or software based methods. Hardware based methods involve using specialized hardware to augment a conventional camera in obtaining images. Some extra information about the image scene can be obtained by inserting some accessorial optical devices into a conventional camera. Software-based multi-focusing methods do not require any specialized hardware. They can be employed directly on images taken with a conventional camera. Many of the existing methods use multiple images of the same image scene for achieving multi-focusing. An example for this is confocal stereo [3] which restores images with high geometric complexity using the confocal constancy property. Such methods have the slight disadvantage of requiring multiple images of the scene, which the user may not always be in a position to provide. Multi-focusing from a single image taken with a conventional camera is a far more challenging problem and is also the objective of this paper. Single image techniques involve using defocus blur as a cue for depth, as the blur is proportional to the depth of the scene. Using the intuitive notion that a blurred ramp edge is originally a sharp step edge, the amount of defocus blur at the edge regions can be estimated. The blur at the edges is then propagated to the entire image to obtain the blur map [4]. In order to, restore the all-focused image after estimating the blur map, many of the existing methods use a de-convolution step. But this de-convolution step yields ringing artefacts in the focused region and low depth of field in the restored image. The method proposed in this paper makes use of the point-to-point blur model [1], which helps avoid the de-convolution step. This reduces halo artefacts in the recovered image and improves the computational efficiency. The blur map is estimated by calculating the amount of blur at the edge regions and then propagating this blur under the guidance of the input image to obtain a full blur map using a matting framework. The other unknown model parameter, diffusion component, is then calculated. The blur map along with the diffusion component and the input image is used to recover the all-focused image according to the point-to-point blur model. For achieving multi-focusing, the depth map of the image scene is required. But there is ambiguity over the focal plane. When an object appears blurred it can be on either side of the focal plane. In this work, this ambiguity is removed by assuming that all of the captured scene objects are located on one side of the focal plane. This works for near or far focused images. But this assumption results in significant errors for mid focused images. The only solution to avoid this ambiguity, in the case of single image method, is user interaction. Using blur map and some original camera parameters fixed for the scene we can calculate the depth map. Multi-focused images can then be obtained using the all-focused image, depth map and modified camera parameters.

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II. POINT TO POINT BLUR MODEL

The multi-focus method proposed in this paper makes use of the point-to-point blur model introduced in [1]. Point-to-point blur model is a defocus blur model derived from the Gaussian model under the local smoothness assumption.

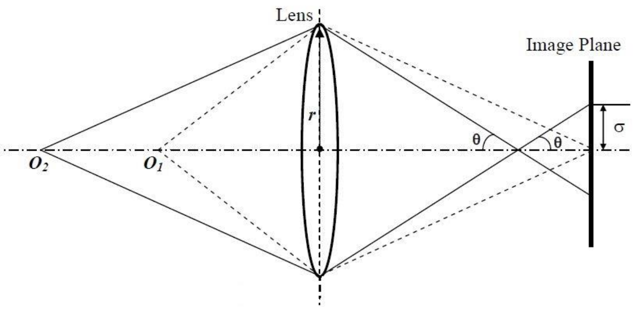

Fig 1. Image formation in a camera

When a photograph is taken with a camera, the lens is focused at a particular plane called the focal plane. This means that the light rays coming from a point on the focal plane will converge to a single point in the imaging plane (where the sensor is located). This will result in a sharp clear image. But if a point lies away from the focal plane the light rays will converge either behind or in front of the imaging plane. This causes the light rays from the point to fall on multiple sensor points resulting in a blurred image. The light spread will be in the form of a circle (of radius σ). As the point moves away from the focal plane, the radius of the light spread (σ) increases and the resulting image becomes more blurred.

The blurred image I_{blur} can be represented as the result of convolution of the clear image I with the point spread function (PSF) of the camera, p:

$$I_{blur}(x,y) = I(x,y) * p(x,y) \tag{1}$$

The PSF is usually modeled as a 2-dimensional Gaussian function:

$$p(x,y;\sigma) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{2}$$

As it can be seen from (1), to obtain the clear image I from the blurred image I_{blur} a deconvolution step is required. The deconvolution step is time consuming and results in halo artifacts in the focused area and low depth of field.

Unlike many of the existing methods, which use the above mentioned blur model, the proposed method follows the point to point blur model developed in [1]. The model is derived under the local smoothness assumption which states that the adjacent pixels within a small window are almost constant. Even though, this is not true for all images, the assumption holds for a majority of images (as is evident from the study conducted on randomly selected 100,000 images in [1]). Under this assumption point-to-point blur model can be derived from (1) and is given by

$$I_{blur}(x,y) = I(x,y)b(x,y) + D(x,y)(1-b(x,y)) \tag{3}$$

where $b(x,y)=1/2\pi\sigma^2(x,y)$ is referred to as the blur map. $\sigma(x,y)$ is blur radius at the pixel position (x,y). $b(x,y)$ denotes the attenuation that the light falling on the pixel at (x,y) suffers because of the spreading. $D(x,y)$ is called the diffusion component. It denotes the component of light from the neighboring pixels that falls on the pixel at (x,y).

III. ALGORITHM

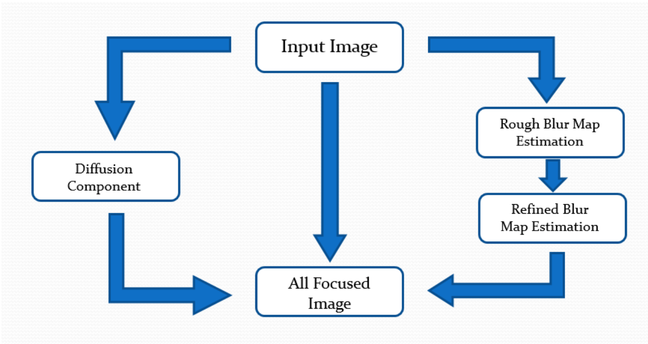

Fig 2. Block diagram of all-focused image retrieval process

A. Rough Blur Map Estimation

In order to obtain the rough blur map, the amount of blur at the edges is calculated under the assumption that a blurred edge was originally a step edge [2]. For this, the edges are first reblurred using two known Gaussian kernels of different variances, σ_1^2 and σ_2^2.

$$\nabla i_1(x,y) = \nabla\left(i(x,y)\otimes g(x,y,\sigma_1)\right)$$
$$\nabla i_2(x,y) = \nabla\left(i(x,y)\otimes g(x,y,\sigma_2)\right) \tag{4}$$

where $g(x,y,\sigma)$ represents the 2D Gaussian kernel with variance σ^2. The ratio of the magnitude of the two reblurred versions is then calculated.

$$k(x,y) = \frac{|\nabla i_1(x,y)|}{|\nabla i_2(x,y)|} \tag{5}$$

Now, this ratio will be maximum at the edges. Making use of this fact, the blur radii at the edges can be calculated as,

$$\sigma(x,y) = \sqrt{\frac{\sigma_1^2 - k(x,y)\sigma_2^2}{1-k^2(x,y)}} \tag{6}$$

The rough blur map can be obtained from the blur radius using the following equation.

$$\hat{b}(x,y) = \frac{1}{2\pi\sigma^2(x,y)} \tag{7}$$

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B. Refined Blur Map Estimation

The rough blur map contains the blur radii at the edge locations of the image. In order to obtain the full blur map, the blur information at the edges is propagated to the entire image using a matting framework under the guidance of the input image. The blur estimation problem can be expressed as the minimization of the cost function *E(b)*.[2]

$$E(b)=b^T Lb+\lambda(b-\hat{b})^T \Lambda(b-\hat{b}) \quad (8)$$

where b^ and b are the vector forms of the rough blur map b^(x,y) and the full blur map *b(x,y)* respectively. *Λ* is a diagonal matrix whose element Λ_{ii} is 1 if a pixel at position *i* is at the edge location and 0 otherwise. λ is a parameter which controls the smoothness of estimation. *L* is the matting Laplacian matrix whose element *L(i,j)* is defined as

$$\sum_{k|(i,j)\in\omega_k}\left(\delta_{ij}-\frac{1}{|\omega_k|}\left(1+(I_i-\mu_k)\left(\Sigma_k-\frac{\varepsilon}{|\omega_k|U_3}\right)^{-1}(I_j-\mu_k)\right)\right) \quad (9)$$

where μ_k and Σ_k are the mean and covariance matrix of the colors in the window ω_k. U_k is a 3 dimensional identity matrix. I_i and I_j are the colors of the input image *I* at pixel *i* and *j* respectively. δ_{ij} is the Kronecker delta. E is the regularization parameter. $|\omega_k|$ is the size of the window ω_k.

The full blur map *b* can be obtained from the following equation.

$$b=\frac{\lambda\Lambda\hat{b}}{L+\lambda\Lambda} \quad (10)$$

C. Diffusion Component Estimation

The diffusion component can be estimated as the average of the average of the adjacent pixels within a small window surrounding the pixel at *(x,y)*. This can be represented as:

$$D(x,y)=\frac{1}{(|\omega_{xy}|-1)}\sum_{(i,j)\in\omega_{xy},(i,j)\neq(x,y)} I_{blur}(i,j) \quad (11)$$

where $|\omega_{xy}|$ is the size of the window centered at the pixel at *(x,y)* and $I_{blur}(x,y)$ is the intensity of the defocused image at the pixel position *(x,y)*.

D. Retrieval of All-focused Image

The clear or all-focused image *I* can be recovered using (3):

$$I(x,y)=\frac{I_{blur}(x,y)-D(x,y)}{b(x,y)}+D(x,y) \quad (12)$$

As can be seen the expression involves a division by *b(x,y)*. In order to avoid division by zero, a lower bound of 0.1 is fixed for the blur map *b(x,y)*.

E. Depth Map Estimation

The depth map can be obtained directly from the blur map using certain camera parameters fixed for the scene that was captured. This makes use of the notion that the amount of blur is directly proportional to the distance from the focal plane. So, blur can be used as a cue for depth. The depth map can be obtained from the blur radius map using the following relation.[1]

$$d(x,y)=\frac{F_0 v_0}{v_0-F_0-b(x,y)f_0} \quad (13)$$

where F_0, f_0 and υ_0 are the focal length, f-number and the distance between the lens and the image plane respectively. These parameters are usually found among the EXIF data that is embedded in the JPEG image file generated by most digital cameras.

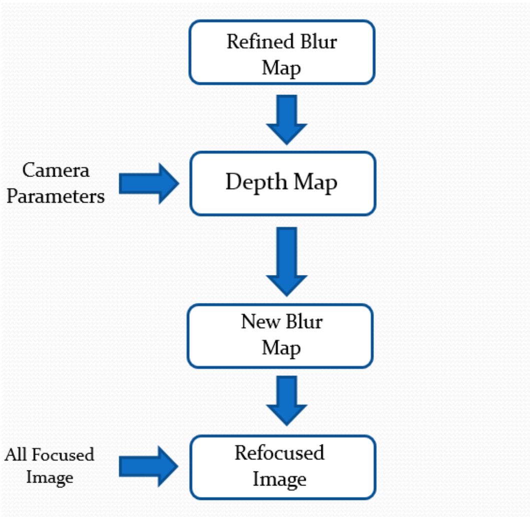

Fig 3. Block diagram of multifocusing process

F. Multifocusing

The first step towards multifocusing is the calculation a new blur map using a set of new camera parameters namely focal length(*F*), f-number(*f*) and distance between image and object plane called flange focal length (*υ*). Changing *υ* changes the plane of focus while changing f changes the depth of field of the image. Once the new camera parameters are defined, the new blur map can be calculated as [1]

$$b_{new}(x,y)=\frac{v}{f}-\frac{F}{f}-\frac{Fv}{f}\cdot\frac{1}{d(x,y)} \quad (14)$$

The new blur map can also be directly obtained from the original blur map without calculating the depth map using (15) [5], but the depth map provides a means of easy verification of the obtained results.

$$b_{new}(x,y)=\frac{v}{v_0}b(x,y)+\frac{F}{f}\left(\frac{v}{v_0}-1\right) \quad (15)$$

where υ_0 and υ are the original and new flange focal lengths, b(x,y) is the original estimated blur map. *F* and *f* are the new focal length and *f*-number respectively. After the new blur map is calculated it can be applied to (3) to obtain the multifocused images.

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IV. EXPERIMENTAL RESULTS

The algorithm was implemented on MATLAB 2011. The experiments were carried out on a variety of images ranging from 250x250 to 600x800 in size. A PC with second generation Intel i7 processor and 4GB of RAM running Windows 7 was used for the experiments.

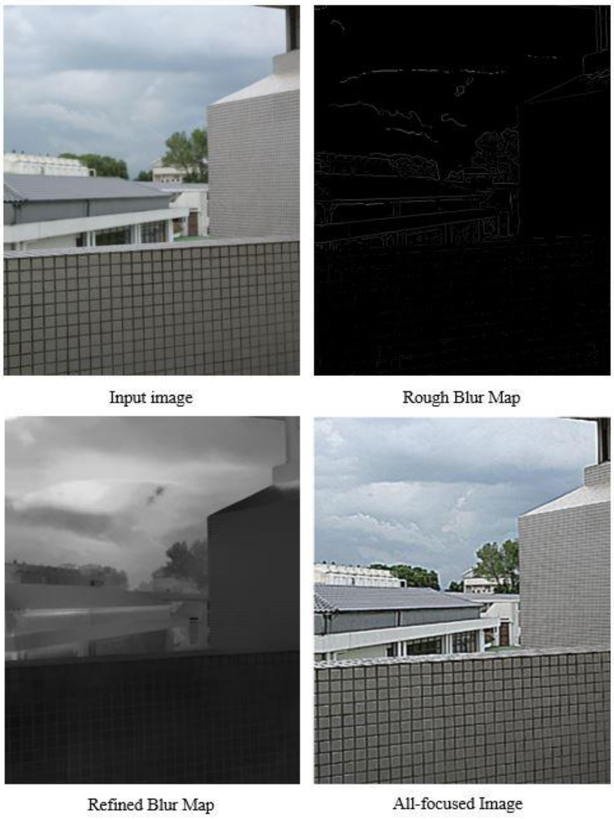


Fig 4. All-focused image from defocused input.

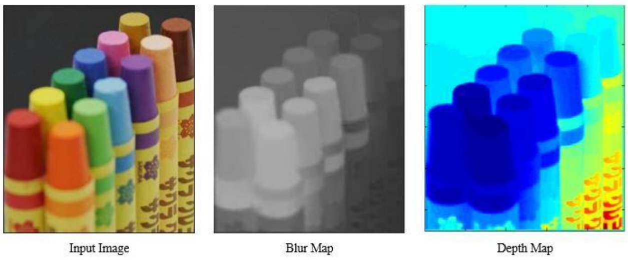


Fig 5. Depth map obtained from blur map

Fig. 4 shows the retrieval of the all-focused image from a defocused input image. Fig. 5 shows the depth map obtained from the blur map along with the corresponding input image. The depth map is represented as a color map with the color change from blue to red indicating an increase in depth. Fig. 6 and Fig. 7 show some multifocusing results that were obtained.

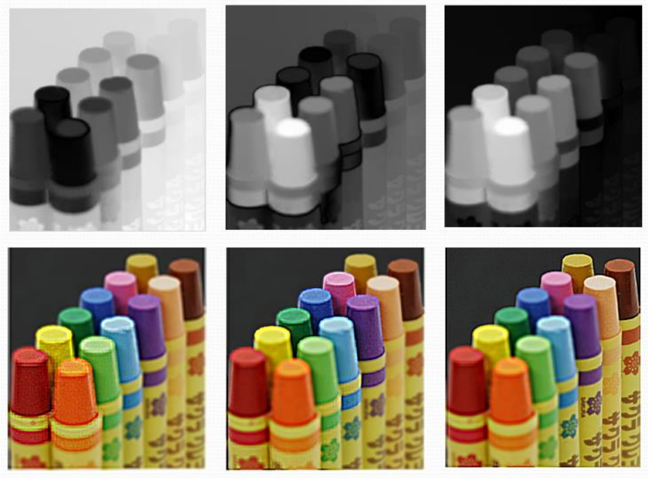
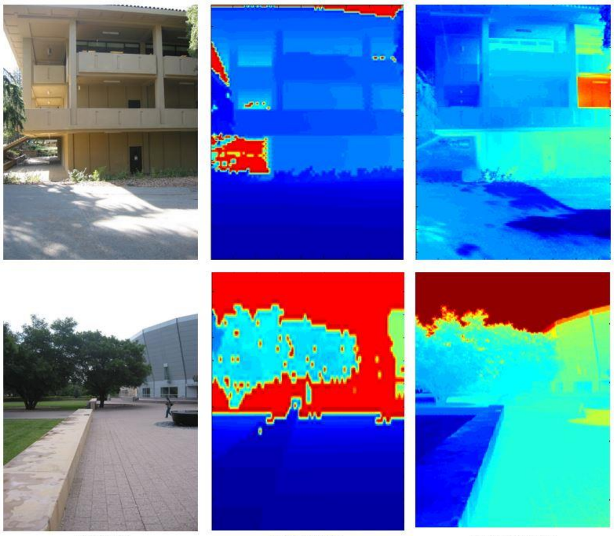


Fig 6. Multifocusing results. Row 1 gives the new blur maps. Row 2 gives the corresponding refocused images.

Fig 6. Multifocusing results. Row 1 gives the new blur maps. Row 2 gives the corresponding refocused images.

In order to check the accuracy of the depth maps obtained, the experiments were conducted on a depth database downloaded from Saxena's website [6]. The depth database consists of images and their corresponding real depth maps obtained using hardware. Fig. 8 shows a comparison of the obtained depth map with the real depth map. As can be seen the proposed algorithm gives fairly accurate results.



Input image Real depth map Obtained depth map

Fig 8. Depth map comparison.

The proposed algorithm also gives high computation efficiency compared to deconvolution based methods and doesn't generate any ringing artifacts in the image. For a 600x800 image the proposed algorithm takes less than 20 seconds to give the final result while the deconvolution based methods take about 1 minute on the aforementioned system.

V.CONCLUSION

This paper puts forward a method for single image multifocusing. The proposed method has the advantage over most existing deconvolution based methods in terms of computational efficiency and introduction of artifacts in the final result. Even though the method does not produce results as accurate as those obtained using hardware or multi-image based techniques, it requires only a single image for multifocusing and does not need any additional hardware.

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