Generation of defocus map of single image using defocus blur

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Abstract

The depth information of any image is crucial part of image processing, projecting 3D images requires this information, and capturing 2D images has not 3D information. So this will lead to create algorithm which will extract depth map from 2D images. This 2D image along with depth map reconstructed from this image will generate 3D image. This depth map could be obtained by various cues present in the images. Getting depth map from 2D images with the help of defocus cue will use blurring of image at edge locations.at edge locations of different segment discontinuity in image pixels observed. We have created different regions of image propagation for good defocus map. Segmentation of images aAlong with Edge detection will target detection of near and far object present in image. This accuracy of defocus map could be improved with the better segmentation ability. Segmenting image into multiple parts is called as a superpixel creation. We have used this superpixel technique.

Index Terms—Defocus estimation, Blur, Cues, Edge Detection, Superpixels

I. INTRODUCTION

In this paper we target to understand problem of image blur which provides vital information for generating relative depths. Generating this defocus map of image is also helpful in various applications in image processing field like background correction, important object detection, refocus, segmentation, matting etc. [8] Defocus blur is identified using input image edge pixel and hence yields a defocus map. Therefore it is highly necessary to have propagation step to spread defocus value over entire image.

A. Related Work

The capability to understand and observed scene in 3D is possible with depth information of images. This depth information can be extract from images using depth cues. There are two types of depth cues, one is monocular in which information perceives using single eye and another binocular in which information perceive using two eyes. S. Zhuo and T. Sim [2] uses monocular cues to estimate defocus map. C. Zhang, Z. Yin, and D. Florencio [6] uses motion parallax cues information to estimate defocus map. J. H. Elder and S. W. Zucker. [16] developed to measure image blur using the first and second order gradients on edges, and from that generate a sparse defocus map.

The defocus blur is most of times estimated with the edge pixels. The outcome of this estimation thus yields a sparse defocus map. Hence, a subsequent propagation step is requires to spread out the sparse defocus values to the complete image. But We observe that the existing estimation methods usually requires a lot of time on the first propagation step, and this will results into limit the applicability of defocus blur estimation. The excessively heavy computational efforts on the propagation cycle encourage us to explore a faster strategy for propagating the sparse defocus map.

B. Our approach

Generally most of the mentioned gradient based defocus map estimation techniques contain two phases of operation. In the first phase creates the sparse defocus blur estimation at edge locations. In the second phase propagates estimated sparse defocus blur over the entire image. The existing methods take long time in the second phase. But, the pixel-level defocus information is not always required in some of the applications, for example foreground/background segmentation and salient region detection. Hence, instead of using, colonization, graph-cuts, or matting Laplacian methods for pixel-level defocus propagation as in the previous work, we use and integrate oversegmentation and transductive inference to achieve faster and efficient propagation at the superpixel level.

Fig 1 (a)

Fig 1 (b)

Figure 1 : Example of defocus map generation

II. OVERVIEW OF APPROACH

Fig.(2) shows our model of defocus map estimation, In this model first image taken for preprocessing which includes some noise removal filters, then we used Edge detection technique to detect edges into images this edge detection output provided to the defocus blur estimation using Gaussian kernel gradient operation. Once defocus blur is detected then image is again oversegmented using SLIC superpixel algorithm. From this superpixel and blur calculation propagation of this algorithm finally generates defocus map.

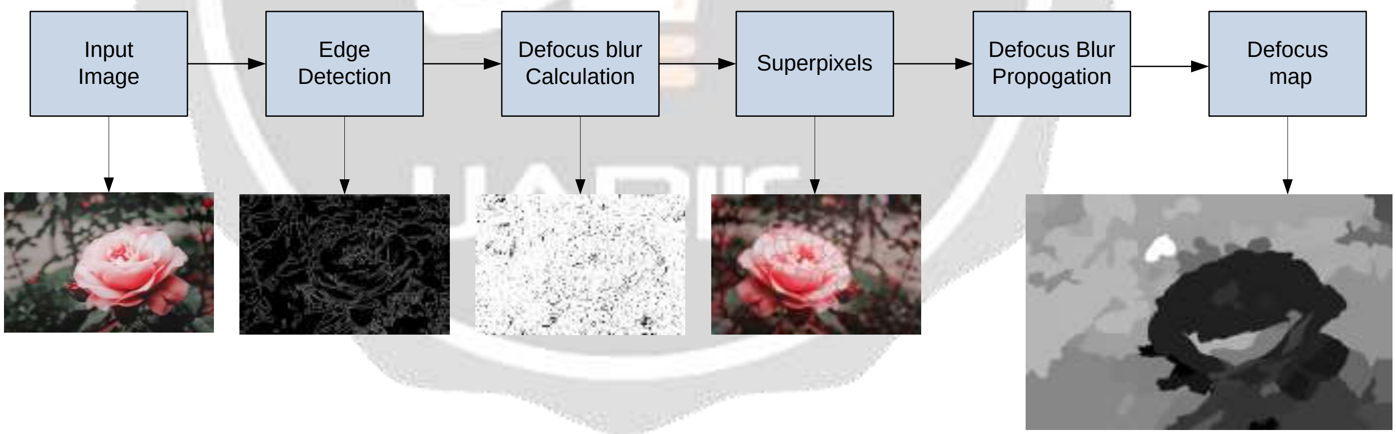

Figure 2 : Defocus map creation model

III. ALGORITHM FOR OUR APPROACH

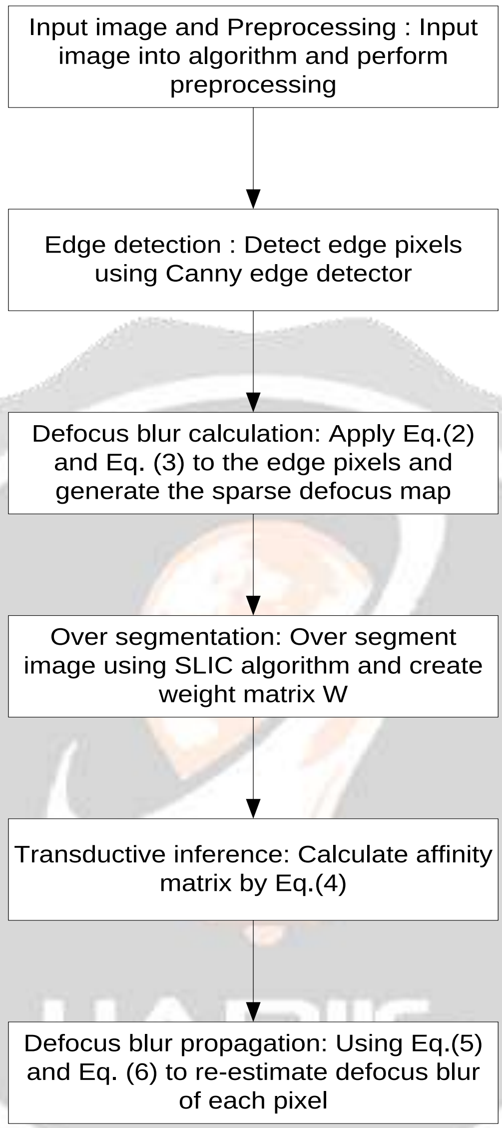

Figure 3 : Algorithm for defocus depth map creation

IV. PRIMARY STAGE DEFOCUS BLUR ESTIMATION

Our methodology includes two cycles, first we performed sparse defocus blur calculations and then we do defocus blur propagation. The first cycle of operation estimates the defocus blur of given image on the edge of pixels, in this method we use gradient based approach. The second cycle of operation includes a new algorithm to propagate the sparse defocus blur created earlier to the complete image.

A. Edge detection

As defocus blur is generated from image edge locations, here we applied edge detector on the image and result into set of E of edge pixels. We applied Canny Edge detectiono technique [9] and structure edge detector estimation method [10] for better performance and efficiency. Outputs of this edge detector have shown in below result section.

B. Defocus blur calculation

We have an edge function $e(x) = \alpha h(x) + \beta$, where α and β denote the amplitude and the offset of the edge respectively, h(x) denotes the step function, and x is a pixel location. The defocus blur can be modeled as a convolution of an edge pixels x with a Gaussian kernel $g(x, \sigma)$, where in standard deviation value σ gained from proportional value of circle diameter c. Also blurred edge is hence defined by $b(x) = e(x) \otimes g(x, \sigma)$. In this case value of unknown standard deviation σ defined by blurriness of an edge pixel and could be used as to represent level of defocus blur which is on that edge pixel.

If we again re-blur given edge pixels using different Gaussian kernel, then in this case gradient of that re-blurred edge represented as

$$\nabla (b(x) \otimes g(x, \sigma_r)) = \nabla (e(x) \otimes g(x, \sigma) \otimes g(x, \sigma_r))$$

$$= \frac{\alpha}{\sqrt{2\pi(\sigma^2+\sigma^2 r)}} \exp\left(- \frac{x^2}{2(\sigma^2+\sigma^2 r)}\right) \qquad \text{……. (1)}$$

Where σ_r denotes as standard deviation of re-blur Gaussian kernel. Zhuo and Sim [2] observed that gradient magnitude ratio R given in original blurred edge with the reblurred edge having maximum value at edge locations. Hence this, maximum value represented by

$$R = \frac{|\nabla b(x)|}{|\nabla b(x) \otimes g(x, \sigma r)|} = \sqrt{\frac{\sigma^2 + \sigma^2 r}{\sigma^2}} \qquad \text{……. (2)}$$

Thus, we calculate this unknown blur σ using gradient magnitude ratio defined as R at edge location with below equation by

$$\sigma = \frac{\sigma r}{\sqrt{R^2 - 1}} \qquad \text{……. (3)}$$

Where σ_r already known value and R can be calculated from gradient of magnitude. Here that Eq. (3) is applicable for the edge locations only. Therefore, intermediate value outcome at current stage is a sparse defocus map on given edge pixels, this is shown in defocus blur model block in Fig. 1.

V. PROPAGATION OF DEFOCUS BLUR

A. Creating superpixels

Target from this step is of first creating the basic units called as (superpixels), and next to define similarity between neighborhood superpixels. Given an image, we first use the SLIC algorithm to oversegment the image into a superpixel set $S = \{ s1, s2, \ldots, sN \}$. As per the superpixel set S, we state a weighted connections of graph $\mathcal{G} = ($ S, □,ω), in which the set of vertex is the superpixel set S and edge set □ containing pairs in adjacent every two superpixels. That, each of vertex S_i given the one single superpixel S, and also each edge $e_{ij} \in$ □ denotes adjacency connection between superpixels s_i and s_j . The weight function ω : □ →[0,1] defines the corresponding weight ω_{ij} in each edge e_{ij} , expressed as terms of feature similarities. We thus define this weight matrix as $W = [\omega_{pq}]\ N\ X\ N$.

B. Transductive inference

The mentioned weight matrix W stated the similarity in between the any of two neighbor superpixels. As per the the transductive inference proposed method by Zhou et al. [2], we can obtain an N-by-N affinity matrix A to defined transductive similar effect between any of two superpixels, However no matter if they are adjacent or not. The affinity matrix A can be stated by

$$A = (D - \gamma W)^{-1} I \qquad \text{…………….(4)}$$

Where *D* is the diagonal matrix along with each diagonal entry equal to the row sum of *W*, γ is a parameter in (0, 1), and *I* is the N-by-N identity matrix. As the affinity matrix is encodes transductive similarity in between any of two superpixels, it is able to adjust defocus blur of any of superpixel combination pair using their affinity *A*.

VI. EXPERIMENTAL RESULTS

We have implemented this algorithm using MATLAB Ver. 2015B software tools. Output of this tool shows images at different stage of algorithm. We have tested this algorithm for multiple images. Sample images were taken from internet database. Execution time required for different stages also displayed in this algorithm. Our target is to create as fast as possible algorithm creation.

In general the computation time of our method to process 800 x 600 Pixel image requires 1 second to process on Intel Core I5-2500 CPU running at 2.4GHz and having RAM of 4GB.

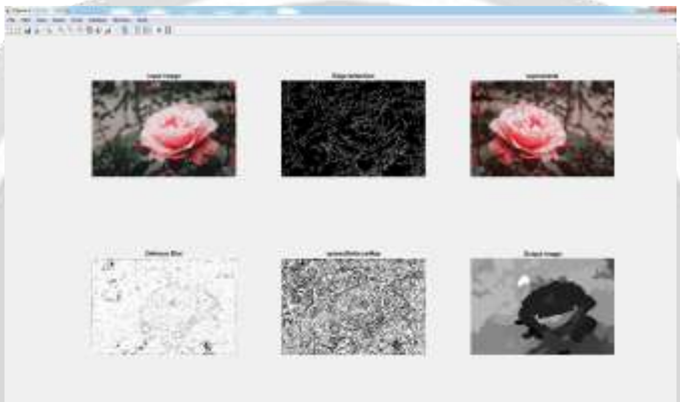

Figure 4 : Experimental results of defocus map generation

More detailed results as follows:

Figure 5 : Input image

Figure 6 : Output defocus map

VII. CONCLUSION

We successfully implemented estimation of defocus map generation from single image using defocus blurring. This algorithm will be future implemented in 2d to 3d image conversion with depth identification. Also we have displayed proposed method can increase speed of the propagation of blur estimation into entire image. Also experimental results show method which we used having well visualization output. This method can be further extending with another additional algorithm to create more accurate depth map for 3D conversion.

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