Rotation Invariant Local Maximum Edge Binary Pattern (LMEBP) based Segmentation of Defocus Blur

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***Abstract*—** In last few years there is lot of development and attentions in area of detecting defocus blur. Defocus is the phenomenon in which image is out of focus and it reduces the sharpness and contrast of image. This blur occur due to the light come from a point outside the focus plane illuminates a non-point region on the sensor known as circle of confusion. Due to defocus blur there is loss of information. No clarity in image features.

Defocus blur is extremely common in images captured using camera. A good photo/image should have the property that the important objects and scenes are clear and sharp. The range of clearness in an image relates to the Depth of Field (DoF) in photography. However, due to variation in Depth of field of image result in blur or inhibit our visual perception of the image scene.

In this we introduced the a novel method of sharpness metric based on local maximum edge binary pattern with rotation invariant(LMEBP) based robust segmentation of defocus blur to separate in and out of focus image regions. In this proposed method the local region of image is represented by local maximum edge binary patterns (LMEBP), which are evaluated by taking into consideration the magnitude of local difference between the center pixel and its neighbors. This LMEBP differs from the existing LBP in a manner that it extracts the information based on distribution of edges in an image. This proposed method exploits that observation of local image patches in blurry regions have significantly fewer regions. So, the metric together with segmentation result in obtain of sharpness edges of defocus blur.

Keywords*—Defocus blur; segmentation; local binary patterns; sharpness metric; image patches; image matting;*

I. INTRODUCTION

One of the most challenging problems for researchers in the field of image processing is image quality assessment. A very important factor in image quality assessment is image sharpness/blurriness. The goal of researchers in the field of image quality assessment is to design and develop algorithms and measures for detecting sharpness and blurriness in an image.

When an image is degraded by excess quantity of blur, identification and classification of elements in the image becomes very difficult. Primary goal of this paper is quantification of the quality of blurred images. The quality score thus obtained can be used for a variety of image processing applications. In this paper we design an image quality measure i.e., sharpness metric for blurred images which will denote the quality of image based on the amount of blurriness in the image.

II. LOCAL MAXIMUM EDGE BINARY PATTERNS

Subrahmanyam et al. [1] have proposed the nearby most extreme edge double examples (LMEBP) for picture recovery and question following applications. In proposed LMEBP for a given picture the main most extreme edge is acquired by the greatness of nearby contrast between the inside pixel and its eight neighbors as demonstrated as follows:

$$I'(g_i) = I(g_i) - I(g_c), \qquad i=1, 2, 8 \tag{1}$$

$$i_1 = \arg_i (\max(|I'(g_1)|, |I'(g_2)|, \ldots, |I'(g_8)|)) \tag{2}$$

Where max(x) calculates the maximum value in an array ‘x’. If this edge is positive, assign ‘1’ to this particular center pixel otherwise ‘0’

$$I^{new}(g_c) = f(I'(g_{i1})) \tag{3}$$

The LMEBP is defined as

$$LMEBP(I(g_c)) = \{I^{new}(g_c); I^{new}(g_1); I^{new}(g_2); \ldots I^{new}(g_8)\} \tag{4}$$

Eventually, the given image is converted to LMEBP image having values ranging from 0 to 511.

After calculation of LMEBP, the whole image is represented by building a histogram supported by

$$HLMEBP(l) = \sum_{j=1}^{N1} \sum_{k=1}^{N2} f(LMEBP(j,k), l), l\varepsilon\, [0,511] \tag{5}$$

Where the size of input image is N1 x N2.

Additionally, the staying seven LMEBPs are assessed utilizing seven most extreme edges (second greatest edge to eighth greatest edge) to get eight LMEBP histograms. Consequently the component vector of the proposed technique is 8 x 512.

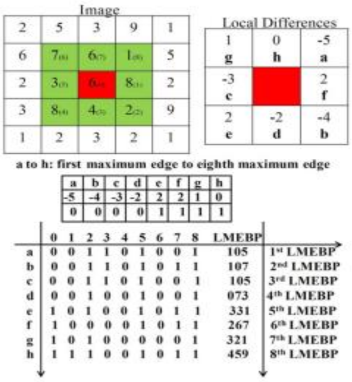

Fig 1: LMEBP calculation for an inside pixel set apart with red shading has been outlined

The uniform pattern refers to the uniform look sample which has limited discontinuities in the circular binary presentation. In this, the sample which has much less than or same to two discontinuities inside the circular binary presentationis takenintoconsideration asthe uniform sample and ultimate patterns considered as non-uniform patterns.

Fig. 2 shows all uniform patters for P=8. The distinct values for given query image is P (P-1) +3 by using uniform patterns. But these features are not rotational invariant.

The rotational invariant patterns ($LMEBP_{P\,R}{}^{riu}{}_{,}{}^{2)}$ can be built by adding all eight patterns in the each row of Fig. 2 as shown in Fig. 3. The distinct values for a given query image is P+2 by using rotational invariant patterns ($LMEBP_{P\,R}{}^{riu}{}_{,}{}^{2)}$. After LMEBP calculation, the joint histogram is constructed between first, second and third LMEBPs for a feature vector generation

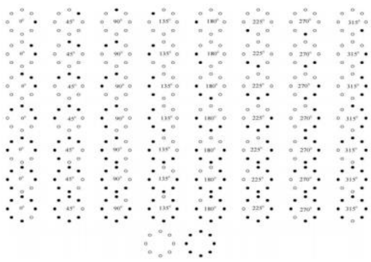

Fig 2: Uniform pattern when p=8. The black and white dots are represent bit value 0 and 1 respectively

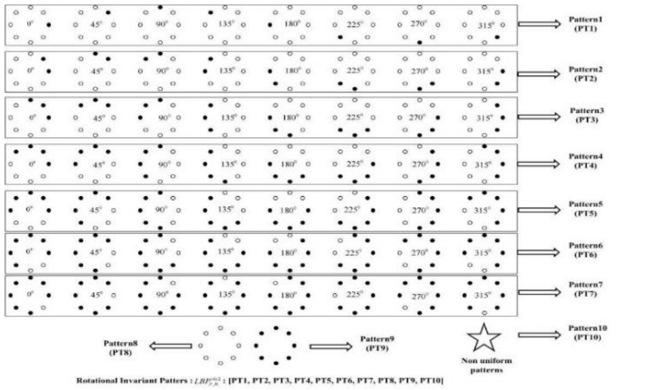

Fig 3: Rotation variant LMEBP Pattern are converted into Rotational Invariant

III. IMAGE MATTING

Matting refers back to the problem of accurate foreground estimation in photos and video. It is one of the key techniques in lots of photo enhancing and film production packages, consequently has been drastically studied in the literature

Correctly setting apart a foreground item from the background involves figuring out both full and partial pixel coverage, additionally known as pulling a matte, or digital matting. This statement was mathematically set up through Porter and Duff in 1984 [1]. They delivered the alpha channel as the way to control the linear interpolation of foreground and heritage hues for anti-aliasing functions while rendering a foreground over an arbitrary heritage. Mathematically, the determined photograph Iz (z = (x, y)) is modelled as a convex combination of foreground photograph Fz and background photograph Bz by using the alpha matte αz:

$$Iz = \alpha zFz + (1 - \alpha z)\, Bz \qquad (6)$$

Wherein AZ may be any value in [0, 1]. If αz = 1 or zero, the pixel z is referred to as specific foreground or precise background, respectively. Otherwise it's referred to as mixed. In most natural photos, despite the fact that most of the pixels are either definite foreground or specific background, appropriately estimating alpha values for mixed pixels is vital for absolutely separating the foreground from the background.

So firstly we are considering sharpness maps are generated using LMEBP. The sharpness metric is computed for a local patch about each image pixel. Sharpness maps are constructed at three scales [s1 s2 s3] where scale refers to local patch size.

A. Matting Initialization

The formation model of image can be expressed as

$$I(x, y) = \alpha_{x,y} F(x, y) + (1 - \alpha_{x,y}) B(x, y) \qquad (7)$$

Where the alpha matte, α x, y, is the opacity value on pixel position(x, y). It can be interpreted as the confidence that a pixel is in the foreground. Typically, alpha matting requires a user to interactively mark known foreground and background pixels, initializing those pixels with α =1 and α =0, respectively. Interpreting "foreground" as "sharp" and background as "blurred", we initialized the alpha matting process automatically by applying a double threshold to the sharpness maps computed in the previous step to produce an initial value of α for each pixel

$$mask^5(x,y) = \begin{cases} 1 & m_{LBP}(x,y) > T_{m1} \\ 0 & m_{LBP}(x,y) < T_{m2} \\ mLBP(x,y) & otherwise. \end{cases}$$

Where s indexes the scale, that is, masks (x, y) is the initial α-map at the s-th scale.

B. Computation

The α-map was solved by minimizing the following cost function as proposed by Levin

$$E\ (a) = a^T La + \lambda\,(a - a')^T (a - a') \qquad (8)$$

Where α is the vectorized α-map, ˆ α=mask I(x, y) is one of the vectorized initialization alpha maps from the previous step, and L LL is the matting Laplacian matrix. The first time period is the term that ensures smoothness, and the second term is the facts becoming term that encourages similarity to ˆ α. The alpha matting changed into implemented at every scale. The very last alpha map at each scale is denoted as α s, s=1, 2, 3

C. Multi-Scale Inference

After determining the alpha map at three different scales, a multi-scale graphical model was adopted to make the final decision. The total energy on the graphical model is expressed as

$$E\ (h) = \sum_{s=1}^{3}\sum_i \left|h_i^s - h_i^{s'}\right| + \beta\left(\sum_{s=1}^{3}\sum_i\sum_{j\epsilon N_i^s}\left|h_i^s - h_j^s\right| + \sum_{s=1}^{2}\sum_i |h_i^s - h_i^{s+1}|\right) \qquad (9)$$

Whereˆ h s i =α s i is the alpha map for scale sat pixel location i that was computed in the previous step, and h s i is the sharpness to be inferred. The first term on the right hand side is the unary term which is the cost of assigning sharpness value h s i to pixel i in scale s. The second is the pair wise term which enforces smoothness in the same scale and across different scales. The weight β regulates the relative importance of these two terms. Optimization of Equation 19 was performed using loopy belief propagation

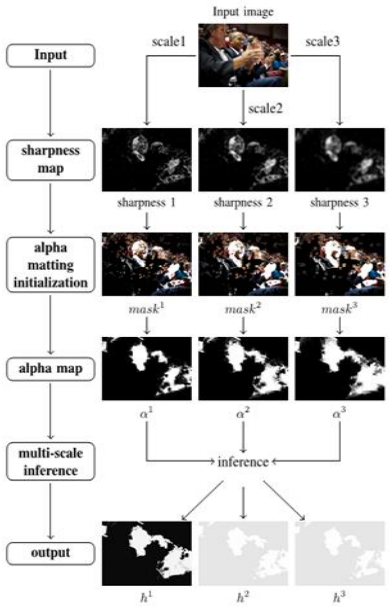

Fig 4: Algorithm steps

For image matting the principle steps are proven on the left; the proper suggests every image generated and its role within the algorithm. The output of the algorithm is h the output of the algorithm is h 3 which is the inferred sharpness map at the largest scale. This is a grayscale image, where higher intensity shows greater sharpness.

D. Parameters consideration

Precision and recall curves were generated for every algorithm through various the threshold used to produce a segmentation of the final sharpness maps (i.e. similar to [3]).

$$\text{Precision} = \frac{R \cap Rg}{R} \qquad \text{recall} = \frac{R \cap Rg}{Rg}$$

Where R is the set of pixels in the segmented blurred region and Rg is the set of pixels in the ground truth blurred region. The values of precision and recall values of LMEBP methods are done better results than compare to existing method.

IV. RESULTS

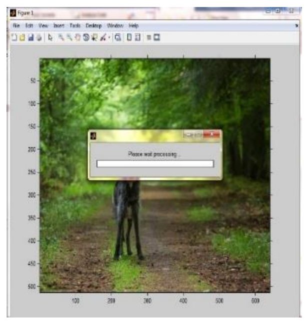

Fig 5: shows the uploaded image and processing

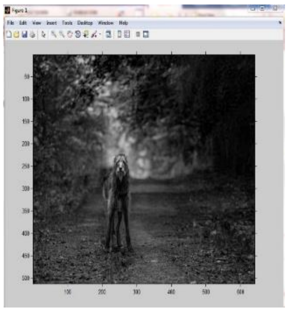

Fig 6: shows grey scale image of original image

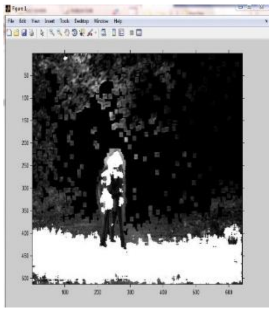

Fig 7: showing image of blur regions

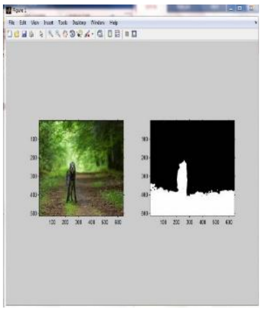

Fig 8: shows the final output with comparison with input

TABLE Parameter consideration for various methods.

Parameter considering	LMEBP METHOD	LBP METHOD
Precision	0.891	0.863
Recall	0.976	0.868

V. CONCLUSION

We have proposed a very simple yet effective sharpness metric for defocus blur segmentation. This metric is based on the distribution of uniform LMEBP patterns in blur and non-blur image regions. The direct use of the local raw sharpness measure can achieve comparative results to the stat-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 better results with the state-of-the-art. Our sharpness metric measures the number of certain LMEBP patterns in the local neighborhood thus can be efficiently implemented by integral images. If combined with real-time matting algorithms, such as GPU implementations of global matting, our method would have significant speed advantage over the other defocus segmentation algorithm

VI. REFERENCES

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Pandula Mounika working as internship training at Hindustan Aeronautics Limited, Balanagar, Hyderabad Under Project SU-30 MKI, Dept. of Weapon Control Systems and Testing. She pursuing her M.Tech from the Department of Electronics and Communications Engineering at Andhra Loyola Institute of Engineering and Technology, Vijayawada, India. She completed B.Tech in Electronics and Communications Engineering from Sir C.R.Reddy college of Engineering, Affiliated to Andhra University, Visakhapatnam in 2015 her areas of interest are Image processing and communication systems.

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