

SEGMENTATION OF FOREGROUND-BACKGROUND USING DEPTH INFORMATION IN MOTION VIDEO

¹U Pavan Kumar, ²Bharathi S H

¹Research Scholar, REVA University, School of Electronics and Communication Engineering,
Bengaluru, INDIA(E-mail: jupiterpavan@gmail.com)

²Professor, REVA University, School of Electronics and Communication Engineering, Bengaluru,
INDIA(E-mail: bharathish@reva.edu.in)

ABSTRACT.

Foreground-background segmentation is a significant problem in computer visualization, and it has numerous applications. We propose a system of Automatic foreground-background segmentation based on strength from coded space. This technique first calculates a coarse in depth map using technique of coded aperture depth origin, then approximation of the broad area of foreground. At last, in order to acquire the foreground, we use the GrabCut algorithm to part the image. The entire progress is fully automatic, without any physical intrusion. Experiments have proved its success. And we also did some easy examples for appliance.

Keywords: Depth from Coded aperture, foreground background segmentation, Grabcut

1. INTRODUCTION

Image segmentation is a very essential field in image processing. It is the fundamental of image analysis. It is generally used in each and every one kinds of field, such as military, medicine, geology. Foreground-background segmentation is a vital problem in computer vision and image segmentation, it has many applications. Using the segmentation consequence, we could understand image mosaic and fusion.

In the paper, we plan to fragment frontal area from foundation. The mix of profundity from coded gap what's more, closer view foundation division is advanced. In the first place, we get a crude profundity outline, is simple to the point that it contains just two sections, frontal area and foundation. As per this crude profundity data, we can figure a rectangular region of intrigue (ROI). At long last, we utilize GrabCut to select the forefront. The entire procedure doesn't require human mediation. Investigation comes about demonstrate the viability of the technique.

Profundity from coded opening is a procedure is produced from Depth from defocus (DFD). DFD was proposed by Pentland in 1987, to compute the separation amongst question and the observer [1]. The measure of fogginess is identified with profundity in the picture from an expansive gap camera. Levin utilized a camera with a coded gap to separate profundity in 2007 [2], which is additionally base on DFD guideline. Levin's technique is embeddings a designed block into an ordinary camera and utilizing this adjusted camera to take just a single picture to get the profundity delineate. Contrasted with conventional DFD, this technique needs less

source picture, in light of the fact that customary strategies require no less than two pictures. In spite of the fact that the estimation takes much time, it is a major development. In any case, the crude consequence of Levin's technique isn't flawless, it needs picture division to enhancement. Levin utilizes the Graph Cuts proposed by Boykov [3]. These days, there are a huge number of millions calculation of picture division. The GrabCut is proposed in 2004 [4], which is produced from Graph Cuts. Grab Cut enhances the division results and makes association less demanding. In this paper, we receive Grabcut to acknowledge closer view foundation division.

2. RELATED WORK

2.1 Depth Extraction

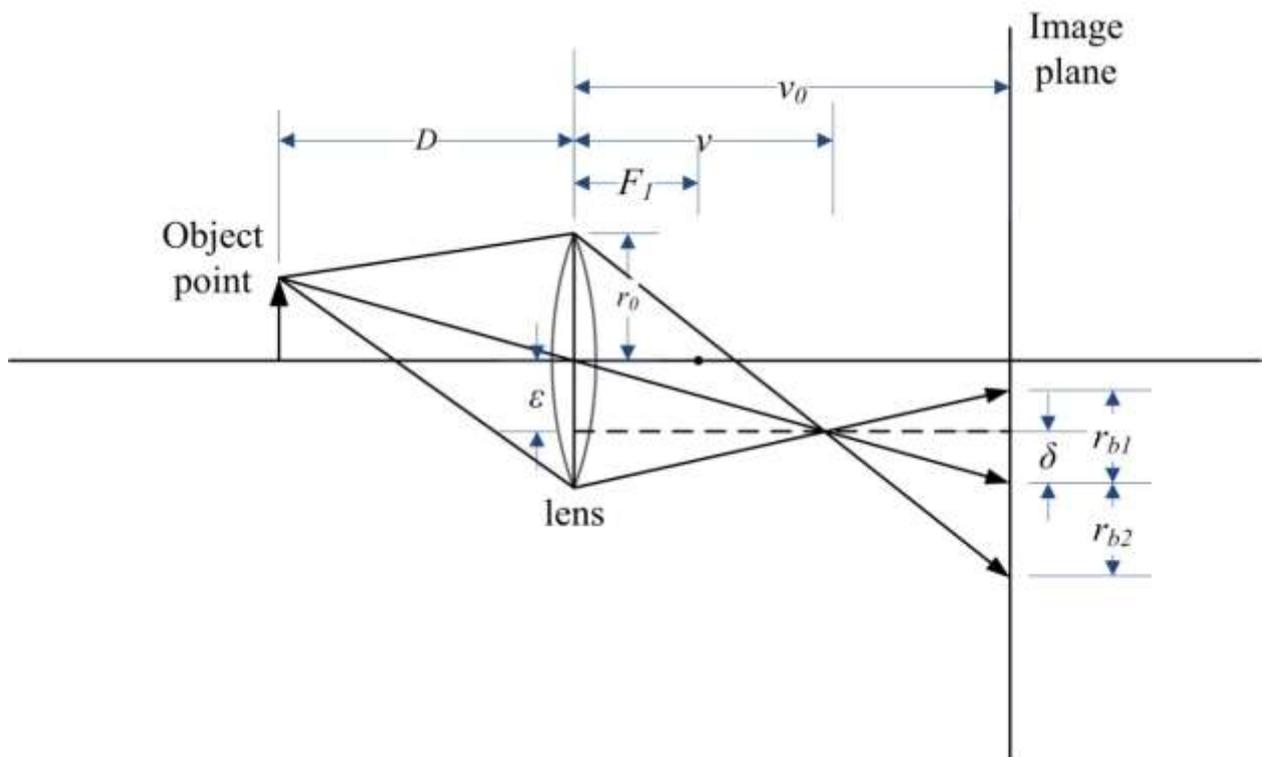


Fig 1 : Optical Model

As the distance between an object and camera is interrelated to the ambiguity of the image. Depth extraction using

a oblique aperture camera is based on this effortless principle. Fig.1 shows a camera mode.

As shown in Fig. 1, a point-like objective at a distance D is frequently mapping to a circle of confusion. The radius of the uncertainty can be consequent according to geometrical optics:

$$p_b = p_0 v_0 \left(\frac{1}{p_1} - \frac{1}{v_0} - \frac{1}{D} \right) \tag{1}$$

We can study from (1) that, in the casing of a predetermined focal length, the extent of uncertainty is only correlated to D , the depth. This is the source of depth-extraction method. In digital image processing, unclear

image can be modeled as convolution:

$$g = h * f$$

(2)

where g is a unclear image, f is a sharp image, h is the convolution kernel. Each position in indistinct image is formed by the interface between equivalent point and the kernel. Due to diffraction, the amount distribution of the uncertainty is not uniform. Usually, f is modeled as a two dimensional Gaussian function. However, for coded aperture, f is related to the example of the aperture, so, it needs calibration. Observably, within a certain range, the scale of confusion is various. And there is a one-to-one correspondence between the scale and depth. Therefore, we could determine the depth by figuring out the PSF on every point in a blurred image.

2.2 Image Segmentation of Grab Cut

Grab Cut is a type of interactive segmentation technique residential from Graph Cuts. It is broaden Graph Cuts to color image, and agree to Gaussian Mixture Model (GMM).The accuracy of segmentation will increase. In accumulation, it desires a user-selected ROI box just to supply relations of information. It is a capable of image segmentation method.

There are few steps need to follow of Grab Cut to obtain RGB foreground.

2.2.1 Initialization

To initialize the background of the image model.

2.2.2 Minimization of Interaction

It is one of the main calculation and its convergence .

2.2.3 User Editing

It is human intrusion for some defective. In a word, GrabCut is a tremendous segmentation method, which also concerns the attention of the user. In the test we find that, frequently behind the first two steps, mainly segmentation outcome can be conventional in conditions of day by day use.

3. METHODOLOGY

3.1 Image Capturing

Using camera with coded aperture to capture a real scene, foreground focused or near focused. This is usually what we do when we take a picture. Obviously, background is defocused.

3.2 To be handled by Rough Depth

3.2.1 Adjust the Point Spread Function (PSF) in Depth Variation

In a certain distance capture an image of a light mark. The outline and the strength of Point Spread Function in this location can be resultant that is the difference between distorted image and sharpening image.

3.2.2 Deconvolution of image by using different scales

The convolution [2] method applying in this methodology. The outcome of deconvolution can be sharpen, the kernel is right for depth. If the scale of kernel doesn't match depth, the result of deconvolution will be still blurred or lead to ringing artifacts.

3.2.3 Convolution

The above results of convolution and consequences of kernels respectively.

3.2.4 Comparison of errors

The source and convolution output are the comparison of errors in Figure 2. Observably, the inaccuracy from wrong kernel is better than from the exact one. There is error of minimum is connected to the right kernel. Later than the resultant be the depth information.

3.2.5 Smooth

By applying filter to smooth we get the resultant map.

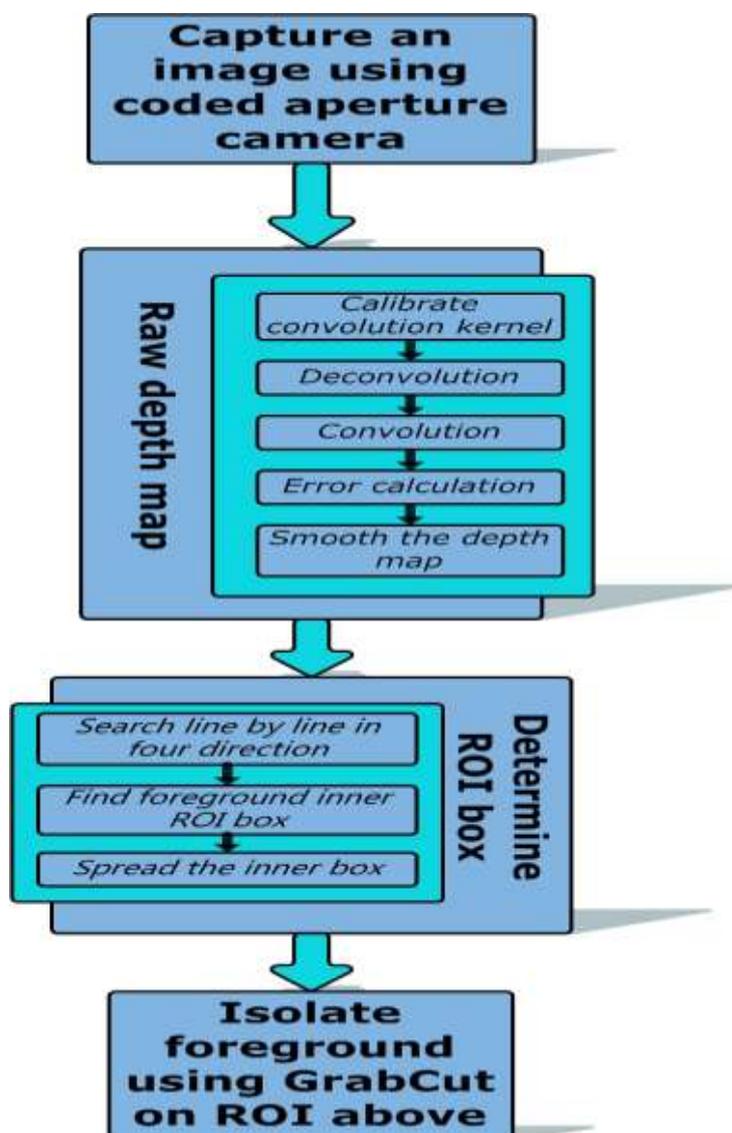


Fig 2 : Proposed Method

3.3 Refinement of Segmentation

The complexity outline smooth-worked, however its edges are not exceptionally great, similarly as Fig. 3(b), in light of the fact that it is influenced by commotion, size of square, proliferation. Hence, this profundity guide cannot demonstrate the closer view and foundation accurately. GrabCut is an incredible strategy in picture division. Typically, focus in the ROI can be sectioned splendidly. We attempt to utilize GrabCut to section them, so our strategy is to discover the frontal area region that is ROI, by utilizing the aftereffect of profundity outline coded opening camera. We exchange our ROI to GrabCut, at that point we could get the division of our ROI.

3.3.1 Searching the border

In raw depth map of foreground pixels we need to search from left to right point by point. Search from left to right line by line, in the raw depth map, for the foreground pixels. And also spot the region to be searched.

3.3.2 Stop condition

Search the foreground pixels until it is superior than the proportion of total foreground pixels in an image. Spot the stop line as internal left border.

3.3.3 Identical to extra directions

By using the related method to estimate the inner right border, inner upper border, inner lower border. In this mode, we can check the ROI too bigger than inaccurate in GrabCut.

3.3.4 Enlarge borders

As above enlarge the four borders then conclude the ROI is obtained. Expand factor is 0.2 to 0.4 empirically.

3.4 To Conclude the Foreground-background Segmentation

Relocate the ROI to GrabCut to get the concluded outcome.

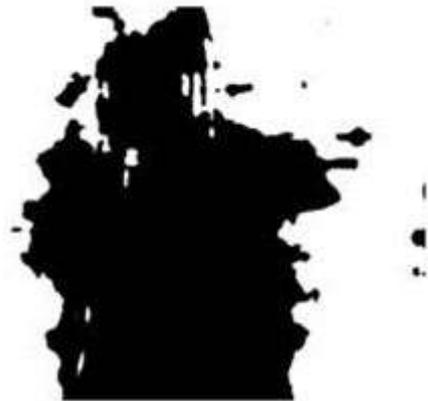
4. EXPERIMENTAL RESULTS

Fig. 3 demonstrates the after effects of an arrangement of tests. The picture is caught open air. The young lady is the objective, clearly is frontal area, in order to a ROI. The coarse division by coded opening camera is appeared in Fig. 3(b). In the outcome, we can generally perceive the area of forefront and foundation. Be that as it may, the division isn't precise to guide to every pixel So it needs alteration. Fig.3(c) demonstrates the ROI comes about. The red wireframe is the inward outskirts which keep the impact of the sporadic division. Also, the blue wireframe (the at long last ROI) can encompass with the young lady, as well as not too huge to trouble for follow-up refinement. So the strategy for deciding the ROI box is successful. The at last division is appeared in Fig. 3(d), we could see that the ROI help the GrabCut discover the frontal area naturally. In any case, we seen that, there is a little locale close to the young lady's arm fizzled division. On one hand, this outcomes from the restriction of crude profundity delineate, yet then again, it caused by lacking of human intercession in GrabCut. So we have much opportunity to get better.

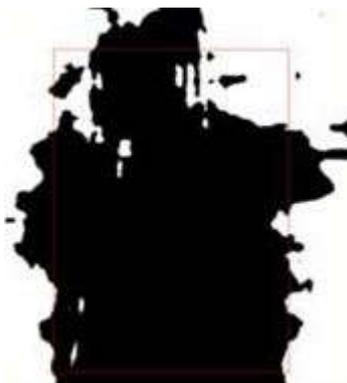
We basically apply this segmentation to restore an extra background, as shown in Fig. 5. In many Scenes we applied automatic foreground-background segmentation.



(a)



(b)



5. ©(d)

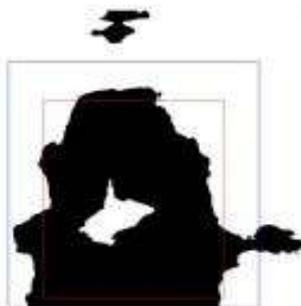
Fig. 3 The outcome of an image (a) is the source picture (b) is the coarse depth map where black represents close and white for far (c) contains the target box, where the red is the effect of the first search, and the blue is the final ROI (d) is the segmentation using the last ROI.



(a)



(b)



(c)



(d)

Fig. 4. Result of another one (a) is the source picture (b) is the coarse depth map where black represents close and white for far (c) contains the target box, where the red is the effect of the first search, and the blue is the final ROI (d) is the segmentation using the last ROI.



Fig. 5 Image Fusion

5. CONCLUSION

Programmed forefront foundation division has numerous applications in our day by day lives. In this paper, we consolidate the profundity from coded opening with forefront foundation division. We first utilize coded opening camera to remove a crude profundity outline. From that point onward, we ascertain the frontal area ROI box in view of coarse profundity. At last, as a great intuitive division technique, GrabCut utilize the ROI programmed chose to acknowledge isolating forefront focus from the foundation. The entire procedure needs no human mediation, so it is programmed.

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