Computational Imaging from Focal Stack Based on Feature Density Measure

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1. Introduction

There are many cues to recovery scene depth such as parallax, perspective and defocused information. Depth from defocus (DFD) and depth from focus (DFF) are the classical methods of a monocular vision which is based on defocused images, and the critical issue is the focus or defocus measure. The techniques of DFD and DFF are attractive because they can avoid the inaccurate matching in stereo vision and achieve the high precision of scene depth map. We applied the feature density to indicate the focus degree of an object point in the focal stack. The focus measure leads to establish computational imaging, including depth estimation and allin-focus imaging algorithms.

2. Computational Imaging from Focal Stack Based on Feature Density Measure

2.1 Feature density measure

The existing edge-based focus measures are usually inaccurate to get the spatial edge focus measure through the partial derivative or gradient in texture regions. The feature points can be detected accurately in the texture region (for example, sum of modified laplace (SML)), which can effectively compensate for the shortcoming of edge-based focus measure.

Image feature refers to texture, shape and color in the image of the object. Scale Invariant Feature Transform (SIFT) is an algorithm to detect and describe local features in images. In this paper, we use SIFT to extract the feature point of the focal stack images. When the image is focused, it includes the richness of detail information, i.e, the number of feature points is largest. When the image is defocused, the number of feature points decreases.

The feature points of the focal stack image in the depth *d* are extracted by the SIFT algorithm, and the feature point coordinate is set to be S(i, j). Then, we define the feature density measure $R_{(x,y)}(d)$ as

$$R_{(x,y)}(d) = \sum_{R_{(i,j)}(d)}^{0} T_{(i,j)}(d)$$
(1)

$$T_{(i,j)}(d) = \begin{cases} 1, & \text{if } S(i,j) \in \Omega(x,y) \\ 0, & \text{otherwise} \end{cases}$$
(2)

Where $R_{(x,y)}(d)$ is denoted by the feature point density of Point (x, y), which means the number of feature points falls its neighborhood $\Omega(x, y)$. The value $R_{(x,y)}(d)$ reaches its maximum when the object point is in focus.

2.2 Computational imaging: scene depth recovery and allin-focus Imaging

The scene depth map and all-in-focus image are generated by acquiring the pixels that possess largest focus measure. For a set of N focal stack images $\{I_k(x,y)|k = 1,2,\dots,N\}$, the focus measure values $\{F_{(x,y)}(d_k)|k = 1,2,\dots,N\}$ $1,2,\dots,N$ are obtained by (1). The scene depth recovery and all-in-focus imaging from focal stack using focus measure is

$$d(x, y) = \arg\max\{F_{(x,y)}(d_k)\}\tag{3}$$

$$I_{AIF}(x, y) = F_{(x,y)}(d(x, y))$$
(4)

Where N is the number of images in the focal stack. $F_{(x,y)}(d_k)$ denotes the focus measure value of the focus stack image in depth d_k . d(x, y) and $I_{AIF}(x, y)$ denote the scene depth map and the all-in-focus image separately.

2.3 Experimental results

We captured the focal stack data to validate the proposed method. The focal stack data of Cans is captured by the Point Gray camera (model: GS3-U3-60S6M-C) and the Myutron prime lens (model: HF5018V) with an exposure time of 10ms and an F number of f/2.

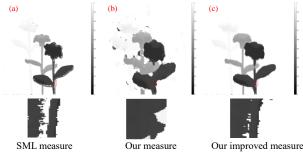


Fig.1 Depth recovery of Flowers

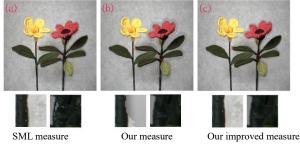


Fig.2 All-in-focus imaging of Flowers

From the closed-up views, the proposed method can effectively recovery the scene depth and all-in-focus image. The proposed method also retains the advantage of the SML algorithm in image edge regions.

3. Conclusions

We propose a novel computational imaging method based on feature density measure from focal stack. Compared to the SML, the proposed method shows a better performance in scene depth recovery and all-in-focus imaging. **References**

- [1] S. Pertuz et al. Pattern Recognition, **46(5)**:1415-1432, 2013.
- [2] W. Huang et al. Pattern Recognition Letters, 28(4):493-500, 2007.