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Depth extraction method based on the regional feature points in integral imaging

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ABSTRACT

In this paper, a novel depth extraction method based on the regional feature point is proposed to enhance the estimation accuracy of the depth and is used to reconstruct 3D scene. Specifically, each elemental image is segmented into many regions firstly and the depth of the object point corresponding to each feature point in each region is extracted, then the depth corresponding to all feature points can be calculated to express the depth corresponding to all object points, which can enhance the accuracy by solving the wrong matching problem in weak texture regions and reduce the amount of calculation. To segment each elemental image properly, we first preprocess each elemental image and segment each elemental image into many regions, then merge some similar regions. Some computational reconstruction experiments are carried to verify the effectiveness of the proposed method.

1. Introduction

Integral imaging is one of the most promising auto-stereoscopic three-dimensional (3D) imaging techniques. Integral imaging has been considered for applications in 3D television and visualization for its inherent advantages, such as full-parallax, continuous viewing points, operating without coherent light, etc. [1]. In these applications, the 3D reconstruction from the planar recorded elemental image array is all essential. But, many integral imaging reconstruction methods, which have been reported by many researchers in the past decades, are mainly reconstructed these images on the given depth plane [2–5], which cannot really recover the 3D information of the object and limits its application. Thus, acquiring depth information from the object and reconstructing a 3D scene are challenging issues in integral imaging.

The first reported work on depth extraction from integral images is that of Manolache et al. [6] in 1999, where the depth estimation task is tackled as an inverse problem of the point spread function of the integral imaging system. But the method can only be applied on the computational generated objects and is ill-conditioned for practical object. Then, many researchers carried out depth extraction process by using stereo-matching algorithm [7–10]. But these methods may be very inaccuracy in weak texture region because that the disparity is hard to find. Zarpals et al. [11] proposed two depth extraction algorithms by anchoring optimizing technique. But, the resolution of the extracted depth map of the above four methods is determined by the resolution of the sub-images, which is very low. Park et al. [12] proposed a method for extracting depth information using a specially designed lens array which is composed by rectangular lens with a long vertical pitch size and fine horizontal pitch size. Hwang et al. [3] proposed a depth extraction method based on imaging property of the integral imaging that only the images reconstructed on the output planes where 3D objects were located are clearly focused, thus the depth data of 3D objects in space can be extracted by discriminating these focused output images from the others by using an imaged separation technique. Jang et al. [4] reported a depth extraction method by using the correlation between an elemental image and a periodic function in computational integral imaging. Yoo et al. [5] described a depth extraction method for 3D objects using block matching between the slice image pairs which are obtained from the windowing technique in computational integral imaging with a microlens array. The above three methods need to reconstruct slice images in different depth and the accuracy is dependent on the interval between the two adjacent slice images. Hence, a novel depth extraction method of high accuracy, high resolution and low amount of calculation is urgently needed.

Accordingly, in this paper, a novel depth extraction method of the complicated scene based on the regional feature point is proposed. In our proposed method, we only need to extract the depth of the object points corresponding to all regional feature points and use the extracted depth to express the depth of each object

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0030-4026/

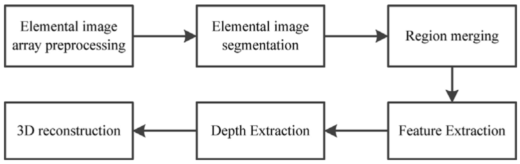


Fig. 1. Schematic diagram of the proposed 3D reconstruction method.

point. The resolution of the depth map is determined by that of the reconstructed 3D scene. Specifically, the proposed depth extraction method and the 3D reconstruction process are described in detail in the next section. To show the verification of the proposed method, some experiments on 3D reconstruction are carried out and the results are discussed in Section 3. Finally, Section 4 concludes this paper.

2. Proposed depth extraction method and 3D reconstruction

The proposed depth extraction method is based on the machine vision theory, such as image segmentation, merging, feature extraction and so on. In our proposed method, we need to extract the depth of the object point corresponding to some necessary feature points, not corresponding to all the points in the elemental image array, and the depth of the object point corresponding to the feature points in each region express the depth corresponding to this region, which can solve the wrong matching problem in weak texture region. Thus, how to segment the elemental image array properly is a key issue to be discussed. Specifically, the reconstruction process can be completed by the following six steps, as shown in Fig. 1. First, we must preprocess the obtained elemental image array to enhance the feature. Second, each elemental image is needed to be divided into many regions using flood fill method. Third, some regions in the above step may be merged into one region. The feature points in all regions are extracted in the fourth step and the depth of these feature points and the object can be calculated in the fifth step. Finally, the 3D scene can be reconstructed in the position of the extracted depth.

2.1. Elemental image array preprocessing

In this step, some edge pixels may be cut from each elemental image first. In the elemental image pickup process, there may be crosstalk and black pixels in the edge of each EI and there may be a slight tilt between adjacent elemental images, which can interface the following feature extraction and influence the final reconstruction. Then, the elemental image array should be preprocessed by the meanshift algorithm [13] to enhance the feature.

2.2. Elemental image segmentation

In this step, each elemental image is segmented into many feature regions. There are many methods can be used to segment the elemental images, such as k-means, flood fill, graph-based segmentation and so on. In this paper, we use flood fill method, which is also called seed fill method.

Specifically, first, a point in the unsegmented region of an elemental image is selected to be a start node and this point is taken as a new region R_1. Second, calculate the color information disparity between the start node and each point in the adjacent region of Region R_1. If the disparity is smaller than the experience threshold value r, the corresponding point must be added to Region R_1. Otherwise, the corresponding point is not added to Region R_1. It is worth noting that the experience threshold value r is must be sufficiently small to insure that each elemental image can be segmented into successively finer regions. Third, the above step is repeated until no more point can be added to Region R_1. Forth, the first step is repeated until each point in the elemental image is segmented into new regions. Fig. 2 shows an example of the segmentation. Fig. 2(a) is an elemental image and Fig. 2(b) is the segmentation of the elemental image.

(a) (b)

Fig. 2. (a) Elemental image; (b) segmentation of the elemental image in (a).

2.3. Region merging

In the above step, each elemental image is segmented into many regions. But, because of the selection of r, some adjacent regions may have similar information, which need to be merged into larger regions. Thus, in this step, the region adjacency graph (RAG) is generated to express the adjacency relation between each region in each elemental image. Then, the adjacent regions may be merged based on the RAG.

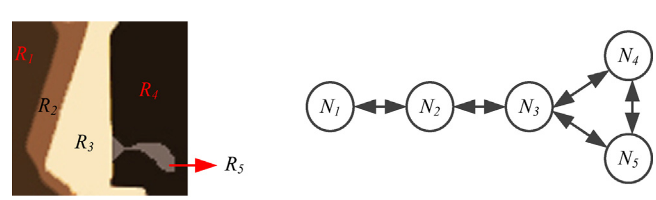
2.3.1. Generation of the region adjacency graph

Regions in each elemental image can be represented by a set of nodes $N = \{N_1, N_2, \ldots, N_m\}$ in the RAG, where the node N_i represents Region R_i and the information of R_i is stored in the data structure of N_i. The line between N_i and N_j means that Region R_i and Region R_j adjacent to each other. Fig. 3 illustrates the generation process of an RAG. Fig. 3(a) is an example of segmentation. The elemental image in Fig. 3(a) is segmented into R_1, R_2, R_3, R_4 and R_5 five regions. As shown in Fig. 3(a), Region R_1 is adjacent to Region R_2. Region R_2 is adjacent to Region R_3. Region R_3 is adjacent to Regions R_2, R_4 and R_5. Region R_4 is adjacent to Region R_3 and Region R_5. Region R_5 is adjacent to Region $R_3$and Region R_4. The information of Regions R_1, R_2, R_3, R_4 and R_5 is stored in the data structure of nodes N_1, N_2, N_3, N_4 and N_5, respectively. Thus, the corresponding RAG can be described by Fig. 3(b).

2.3.2. Region merging in an elemental image

In this section, try to merge the current region with the adjacent regions in the same elemental image which are captured the same object information as the current region. Then, these similar regions in the same elemental image are merged [13].

Assuming the image region having a constant gray value, independent on each other, additive and zero mean Gaussian noise pollution, the gray value of the region are normal distribution. Assuming that the two adjacent regions R_1 and R_2 have m_1 and



(a) (b)

Fig. 3. (a) Segmentation of an elemental image; (b) region adjacency graph of corresponding regions in (a).