컴퓨터 집적 영상 기술에서 Recursive PCA를 이용한 부분적으로 가려진 3D 물체의 완전 요소 영상의 복원

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Reconstruction of Full Elemental Images from Partially Occluded 3D Object in Computational Integral Imaging by use of Recursive PCA

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Abstract

In this paper, we propose a new method of recovering full elemental images from partially occluded 3D object in computational integral imaging. We first detect the regions of occlusion and generate the entire elemental images of 3D object with occlusion by recursive error compensation using PCA reconstruction. The experimental results show that the proposed method provides an effective solution to the problem of partially occluded 3D object recognition.

1. Introduction

The integral imaging method is used commonly and widely among 3D imaging techniques because it provides auto-stereoscopic and parallax provision [1]. For 3D object recognition using integral imaging, computational integral imaging (CII) systems have been introduced [2]. It is composed of the optical pickup and the computational integral imaging reconstruction. In optical pickup, 3D object is recorded as the elemental images through a lenslet array. In the computational reconstruction process, the elemental images are digitally processed by use of a computer where 3D images can be easily reconstructed at any reconstruction output plane without optical devices.

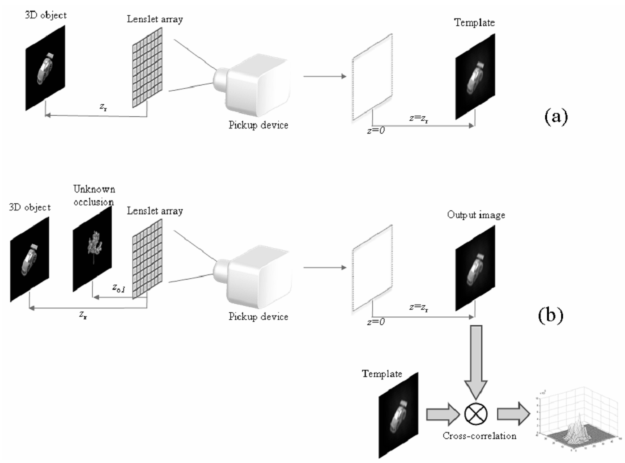
As a good application of CII, a study to recognize a 3D object that is partially occluded in a given scene has been proposed [2,3]. The main principle of recognition for a partially occluded object is to produce a series of plane images computationally and then to correlate them with original 3D object. In partially occluded 3D object recognition, however, the unknown occlusion makes the resolution of computationally reconstructed plane images degraded seriously because it hides the 3D object to be recognized. Recently, to solve this problem, we proposed an occlusion removal technique for improved recognition using CII [3]. In the proposed technique, we eliminated the unknown occlusion using sub-image block matching in the elemental images and to reconstruct 3D images computationally. Then, resolution-improved 3D plane images were reconstructed through the computational reconstruction process. In fact, occlusion-removed elemental images have partially information loss because the pixels represented by occlusion become zero value.

In this paper, we propose a method of recovering full elemental images from partially occluded 3D object in computational integral imaging. We first detect the regions of occlusion and generate the entire elemental images of 3D object without occlusion by recursive error compensation using PCA reconstruction. To show the usefulness of the proposed method, we carry out the experiments and its results are presented.

2. Review of CII system for partially occluded object recognition

The main idea in partially 3D object recognition using CII is the possibility to obtain the reconstruction of the 3D plane image of interest. Recognition system using CII can be divided into two steps as shown in Fig. 1.

In the first step of Fig. 1(a), the recognized 3D object is picked up by a lenslet array and recorded by a CCD camera. The captured image is referred as reference elemental images. Each elemental image in the reference elemental images has particular perspective about the 3D object. Then, using the reference elemental images, the 3D image can be reconstructed digitally at the certain distant, where the 3D object was located. This reconstruction 3D object is called the template which stored for recognition step.



(Figure 1) Principle of CII (a) Generation of template (b) Recognition

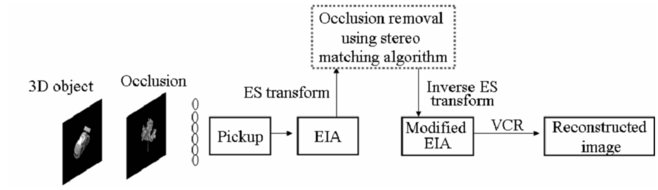
In the second step as shown in Fig. 1(b), target objects having occlusion and the 3D objects are recorded as the target elemental images. Using computational reconstruction [2] of Fig. 1(b), the target output image is reconstructed at the distance of the 3D object. Once an output image is obtained, the correlation process can be performed between the template and the output image. From the correlation results, 3D object recognition can be done.

When the output image is reconstructed in the second step, occlusion degrades the resolution of reconstructed images. To improve the recognition performance, we may reduce the image degradation effect by occlusion.

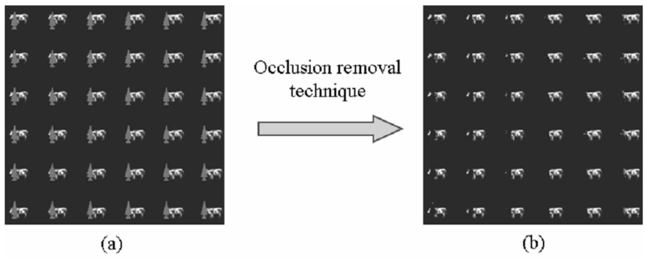
In our previous study [3], we presented an occlusion removal method by enhancing the output image through the elimination of the unknown occlusion. The principle of the CII system using the occlusion removal method is shown in Fig. 2. If the system is compared with the conventional CII system, there are two additional processes to eliminate the unknown occlusion into elemental-images. The first process is to use a computational transform between the elemental images and sub-images. The second process is to remove the unknown occlusion in the sub-images using disparity information by the sub-image block matching algorithm, which is well known in the stereo vision.

After applying the sub-image block matching between two sub-images as shown in Figure 3(a), we extract the depth map between them. Based on the extracted depth map, we can perform segmentation of occlusion and then remove it. This process is repeated for all the sub-images. As a result, we obtain the modified sub-image array with occlusion object eliminated as shown in Fig. 3(b).

To get the desired output image in CII, the modified sub-images are applied to the computational integral imaging method. Thus, the image reconstructed from the occlusion-removal method is more clearly obtained. This improves the resolution of reconstructed image.



(Figure 2) Conceptual diagram for the occlusion removal method in CII



(Figure 3) (a) Original sub-images (b) Occlusion-removed sub-images

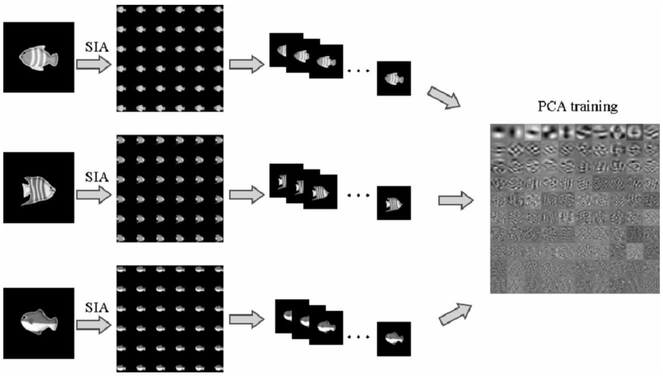
3. Reconstruction method of occlusion-removed sub images

This paper presents a new method of recovering full elemental images without occlusion from partially occluded 3D object in computational integral imaging. This method is based on a recursive application of PCA reconstruction and error compensation to generate the removed part from occlusion-removed elemental images as shown in Fig. 3(b).

The proposed method is composed of an offline process where eigenvectors generated from a set of training reference sub-images and online process where the error of the occlusion-removed sub-images compensated recursively.

3.1. Offline process of PCA

The offline process of PCA is shown in Fig. 4. Given a set of training sub-images generated from 3D objects, the reference images taken from all the sub-images produced by every training image. Then, each image is represented as a column vector. After compute the mean value of the images and subtract each image with the mean value, arrange all the reference images become a single matrix (A). Finally, we compute eigenvectors of the covariance matrix of A matrix [4].



(Figure 4) Diagram of offline process using PCA

3.2. Recursive PCA reconstruction

After the region of occlusion has been extracted, the occlusion-removed sub-image can be compensated using the reconstructed sub-images.

Firstly, the eigenvector of training sub-images is trained and the mean sub-image and the eigenvectors are stored. The input sub-image with occlusion is then reconstructed using PCA method [4].

$$\hat{X}^1 = m + \sum_{i=1}^{k} y_i^0 u_i \quad (1)$$

Here, $\hat{X}$ is the reconstructed image from an input image, m is the mean sub-images and k is the number of the eigenvector. y is the coefficient onto each eigenvector which can be computed by (2) and u is each eigenvector.

$$y_i^0 = u_i^T (X^0 - m) \quad (2)$$

Next, the region of occlusion is compensated suing the reconstructed sub-image obtained by PCA as given by Eq. (3)

$$X^1 = w \cdot X + (1 - w) \cdot \hat{X}^1 \quad (3)$$

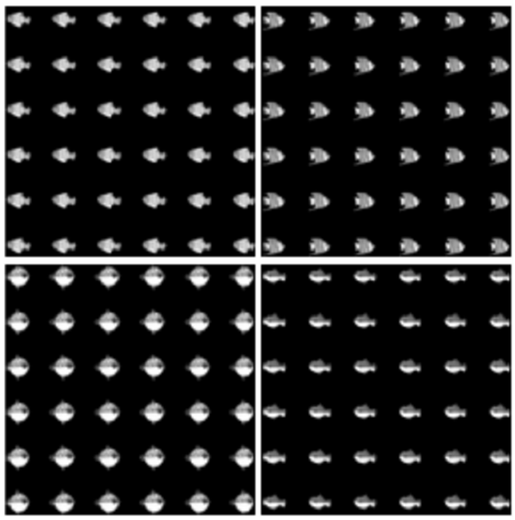
Here, X means the original sub-image and the superscript i is represented X at i-th iteration. And w is weight parameter in range 0-1.

Finally, the compensated image is reconstructed again by simple PCA method to finish an iteration. The iterations repeat until there is no big difference between current compensated image and previsou compensated image.

4. Experimental Result and Analysis

For the experiment, we used 4 different fish images. Each fish image was captured under the pickup system as shown in Fig. 2. The distance between lenslet array and the pickup plane is set by 3 mm and the distance between lenslet array and reconstruct plane is set by three different distance 45 mm. The elemental images of each fish image were computationally synthesized and it has 900×900 pixels. Then each image is transformed into 36 sub-images using the sub-image transform [3] as shown in Fig. 5. Thus, we have 144 training reference images.

In the first experiment, the offline PCA process was performed using the training reference images. After doing the offline process, the eigenvector was stored in a computer.

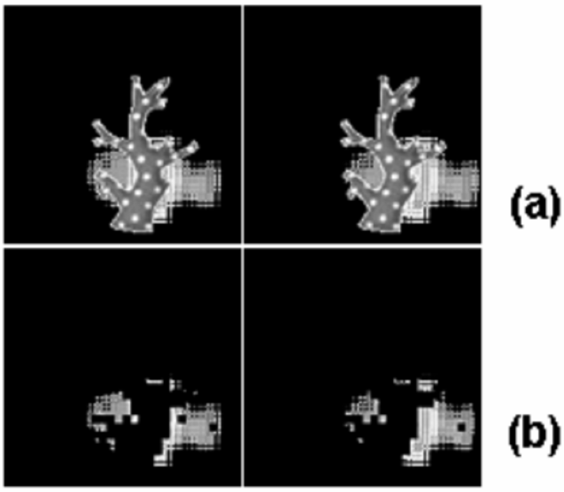


(Figure 5) Four kinds of fish for the training images.

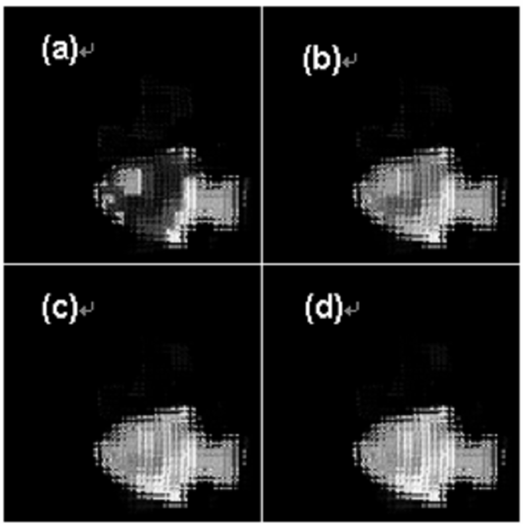
Next, for the online process, we obtained the elemental images for fish with occlusion and transformed it into sub-images. The distance between the occlusion reconstruct plane and the lenslet array is set by 18 mm. Two of sub-images are shown in Fig. 6(a). We applied the block matching to those two images and then obtained occlusion-removed sub-images. As shown in Fig.

6(b), occlusion-removed sub-images have black regions where occlusion exits after eliminating it.

Finally, we reconstructed compensated sub-images by using the recursive PCA method. The iterations repeated until there is no big difference between the compensated images and the previous images. Examples of the compensated images according to the iteration are shown in Fig. 7. We measured PSNR between the original fish images and reconstructed one. The calculated results are shown in Table 1. From Fig. 7 and Table. 1, it is seen that the image quality of the reconstructed images improved significantly after using the recursive PCA method.



(Figure 6) (a) Examples of sub-images for fish with occlusion, (b) after occlusion removal using the block matching.



(Figure 7) Compensated fish images after (a) 1st iteration, (b) 5th iteration, (c) 10th iteration, (d) 15th iteration,

Table1. PSNR results.

	Original sub-images	Compensated sub-images
Fish 1	22.54	27.15
Fish 2	22.76	30.91
Fish 3	23.72	28.57
Fish 4	22.56	31.79

6. Conclusion

In conclusion, we proposed a method to obtain the compensated sub-images using the recursive PCA method for the use of partially occluded 3D object recognition based on computational integral imaging. To show the usefulness of the proposed method, we carried out the experiments and its results show hat the image quality of the reconstructed images improved significantly after using the recursive PCA method.

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