Optics Communications 283 (2010) 2084–2091

Contents lists available at ScienceDirect

Optics Communications

journal homepage: www.elsevier.com/locate/optcom

Enhanced computational integral imaging system for partially occluded 3D objects using occlusion removal technique and recursive PCA reconstruction

Byung-Gook Lee, Liliana, Dong-Hak Shin *

Department of Visual Contents, Dongseo University, San69-1, Jurye2-Dong, Sasang-Gu, Busan 617-716, Republic of Korea

ARTICLE INFO

Article history:
Received 28 September 2009
Received in revised form 19 January 2010
Accepted 19 January 2010

Keywords:
Integral imaging
Lenslet array
Occlusion removal
3D object recognition
PCA

ABSTRACT

In this paper, we propose an enhanced computational integral imaging system by both eliminating the occlusion in the elemental images recorded from the partially occluded 3D object and recovering the entire elemental images of the 3D object. In the proposed system, we first obtain the elemental images for partially occluded object using computational integral imaging system and it is transformed to sub-images. Then we eliminate the occlusion within the sub-images by use of an occlusion removal technique. To compensate the removed part from occlusion-removed sub-images, we use a recursive application of PCA reconstruction and error compensation. Finally, we generate the entire elemental images without a loss from the newly reconstructed sub-images and perform the process of object recognition. To show the usefulness of the proposed system, we carry out the computational experiments for face recognition and its results are presented. Our experimental results show that the proposed system might improve the recognition performance dramatically.

1. Introduction

The integral imaging method is widely used among the recent 3D imaging techniques because it provides auto-stereoscopic and parallax image in space [1–6]. It is applied to various applications such as 3D display, 3D object recognition and so on [2–13]. For 3D object recognition using integral imaging, the concept of the computational integral imaging (CoII) systems have been introduced [8]. It is composed of the optical pickup and the computational integral imaging reconstruction (CIIR) process. In the optical pickup, a 3D object is recorded as the elemental images through a lenslet array. In the CIIR, the elemental images are digitally processed by use of a computer where 3D images can be easily reconstructed at a desired reconstruction plane without optical devices.

As a good application of CoII, a study to recognize a 3D object that is partially occluded in a given scene has been proposed [8,10]. 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 the original 3D object. In the 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 CoII [14]. 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, the resolution-improved 3D plane images were reconstructed through the computational reconstruction process. However, the occlusion-removed elemental images have partially information loss because the pixels represented by occlusion are removed and thus useless in the CIIR process.

In general, the CoII system can utilize the prior knowledge of 3D objects to be recognized. If the system learns the prior knowledge from the given training objects, the occluded regions in the elemental images can be recovered by comparing the prior knowledge for the training 3D objects. If the CoII system has such ability for occlusions, it is expected that the recognition performance can be improved and the applicability of the system can be extended.

In this paper, to improve the recognition performance of CoII system, we propose a new CoII system by both eliminating the occlusion in the elemental images recorded from the partially occluded 3D object and then recovering the entire elemental images of the 3D object. In the proposed system, we first record the elemental images for partially occluded object using the CoII system and then eliminate the occlusion within the recorded elemental images. To generate the removed part from occlusion-removed elemental images, we use a recursive application of principal component analysis (PCA) reconstruction and error compensation. Finally, we obtain the entire elemental images and perform the recognition process. To show the usefulness of the proposed system, we carry out the experiments for face recognition and its results are presented.

* Corresponding author.
E-mail address: shindh2@dongseo.ac.kr (D.-H. Shin).

0030-4018/$ - see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.optcom.2010.01.044

2. Review of CoII system for partially occluded 3D object recognition

The main principle of partially occluded 3D object recognition using the CoII is to reconstruct the 3D plane images for partially occluded 3D object and perform the recognition by comparing the reference plane images of 3D object to be recognized [8,10]. Generally, the CoII-based 3D object recognition system can be divided into two steps as shown in Fig. 1.

In the first step of Fig. 1a, the 3D object to be recognized is picked up by a lenslet array and recorded by a CCD camera. The captured image is referred as the reference elemental images. Each elemental image in the reference elemental images has particular perspectives of 3D object, which provide the 3D information including the distance where 3D object is located. Then, using the reference elemental images, the 3D plane image can be reconstructed with computer digitally at the distance where the 3D object was originally located. The computational reconstruction process is based on CIIR [8]. In CIIR process, first, each elemental image is projected inversely through the corresponding pinhole. Next, when an image is reconstructed on the output plane of z from the pinhole array, the inversely projected elemental image is digitally magnified by a factor of z/g where z are g are the ratio of the distance between the virtual pinhole array and the output plane to the distance between the pinhole array and the elemental images, respectively. Finally, the enlarged elemental images are overlapped each other and summed at the corresponding pixels of the output plane. To obtain a reconstructed plane image of a 3D object at the distance of z, the same process must be repeatedly performed to all of the picked up elemental images through each corresponding pinhole. This reconstructed plane image is called the template, which is stored for the next recognition step.

In the second step as shown in Fig. 1b, the target objects composed of an occlusion and 3D object to be recognized are recorded as the target elemental images. Using CIIR process, the target plane image is reconstructed clearly at the distance z of the 3D object. Once an output plane image is obtained, the correlation process can be performed between the stored templates and the output plane image. From the correlation results, 3D object recognition can be done.

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

3. Enhanced CoII system

3.1. System structure

In this paper, we present a new CoII system of improving the recognition performance by eliminating occlusion by using and recovering the full elemental images without occlusion from partially occluded 3D object. To do so, we use both an occlusion removal technique [14] and a recursive application of PCA reconstruction [15,16] to generate the removed part from occlusion-removed elemental images.

The proposed system is largely composed of two processes as shown in Fig. 2. One is an offline process where the reference templates for the 3D objects to be recognized are generated and their eigenvectors generated from a set of training reference subimages. The other is an online process where the occlusion in elemental images is removed, the error of the occlusion-removed subimages compensated recursively and the object recognition is performed using CIIR.

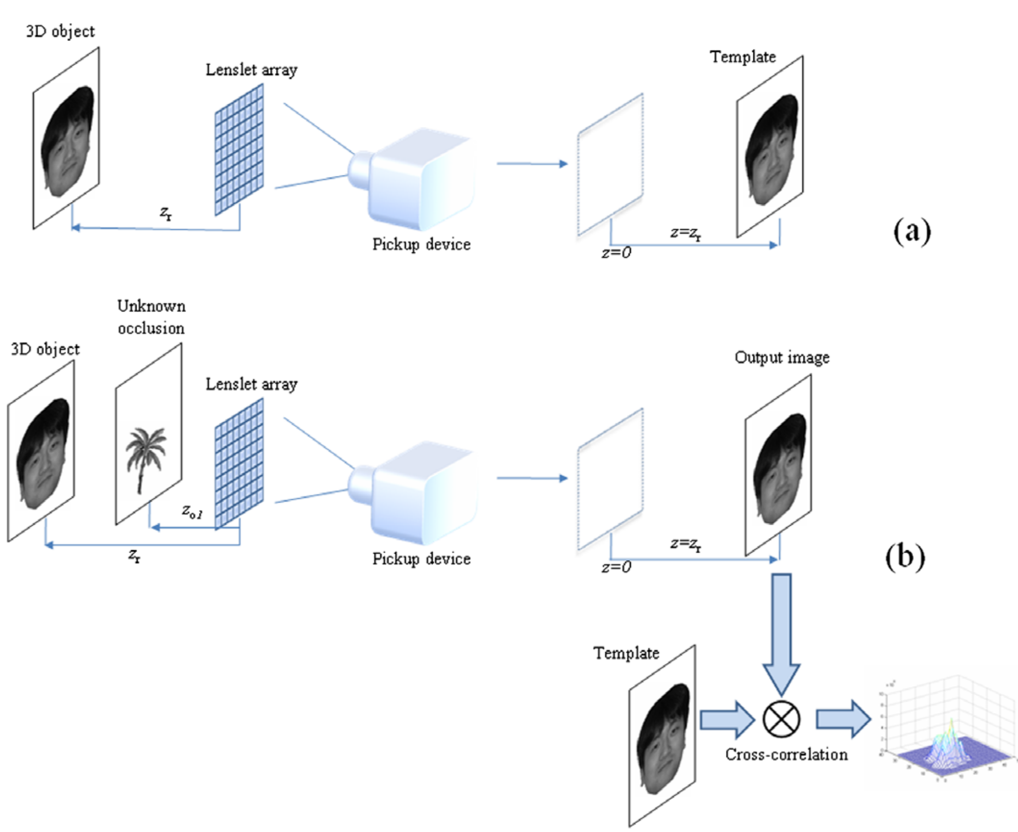

Fig. 1. Principle of CoII (a) generation of template (b) recognition.

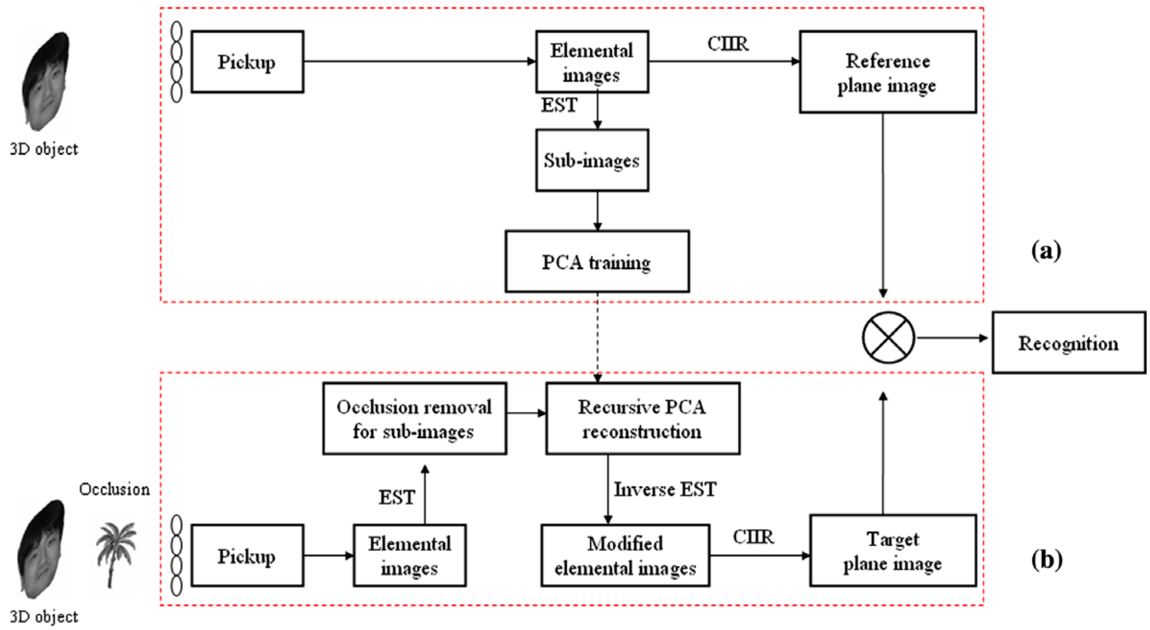

Fig. 2. Conceptual diagram of the proposed CoII system (a) offline process (b) online process.

3.2. Offline process

The offline process is shown in Fig. 2a. Here, we first capture reference 3D objects as the elemental images. Then we use the recorded elemental images for two different ways. One is to reconstruct the template using the CIIR method. This is identical with the conventional CoII system. The other is to generate the eigenvectors from a set of reference templates for the next online process.

Now, we explain the generation of eigenvectors from a set of reference elemental images in detail. First, the recorded elemental images are transformed into sub-images [14] because the sub-image represents the perspectives of 3D object. This transform is call elemental-image to sub-image transform (EST). The EST is a kind of computational pixel recombination process [14,17]. That is, we extract the same position for all of the elemental images and a collection of pixels of same position is obtained as sub-images.

Next, a set of calculated sub-images is applied to the PCA training. The PCA training produces a set of eigenvectors for the next online process using many sub-images obtained from the reference 3D objects. The detail PCA training is shown in Fig. 3. We take each sub-image as the reference trained image (X_k). The sub-image array is assumed to be composed of K block images of size N (=$d \times$ d) pixels. The k-th block image is considered an N-dimensional vector. We represent N-dimensional vectors to each of sub-image K. Let us each of sub-image X_k (k = 1,2, ..., K). The average vector of X_k is given by

$$m = \frac{1}{K}\sum_{k=1}^{K} X_k \tag{1}$$

Next, the average vector is removed from the sub-images. This represents F_k.

$$F_k = X_k - m \tag{2}$$

And, the covariance matrix of sub-images becomes

$$Q = \sum_{k=1}^{K} F_k^T F_k = F^T F. \tag{3}$$

where $F = [F_1, F_2, \ldots, F_K]$ has $N \times N$. From Eq. (3), eigenvalue and eigenvector are computed. The eigenvector V_i can calculated as follows:

$$F^T F V_i = \lambda_i V_i \tag{4}$$

where λ_i is the eigenvalue. Since N is too large, this calculation would be impractical to implement. A computationally feasible method was used to find out the eigenvectors. In other words, consider the covariance matrix as FF^T instead of F^TF. Premultipying Eq. (4) by F, we have

$$FF^T F V_i = \lambda_i F V_i \tag{5}$$

From Eq. (5), λ_i is the i-th eigenvalue and the i-th eigenvector is given by

$$u_i = F V_i \tag{6}$$

After we get the eigenvectors (u_i), the normalized eigenvectors are used as the new basis. Then, each of the reference trained images is projected on the new basis using Eq. (7).

$$y_i = u_i^T (X - m) \tag{7}$$

where u_i means i-th eigenvector and y_i is i-th element of the coefficients y toward u_i. And m is the average of all reference images. The result is a set of coefficients (projection) of the reference image onto the new basis. Since the new basis reduces the redundant information, the number of the coefficient is less than the original data. For the use in the next online process, the coefficients and eigenvectors of all the reference objects are stored in the computer.

3.3. Online process

Now, we consider the online process as shown in Fig. 2b. Let us assume that the unknown occluding object and a target object are located at arbitrary distances z_o and z_r, respectively. Then, these objects are picked up by using a CCD camera. This pickup process provides us target elemental images. The target elemental images are transformed into target sub-images using EST. Since target sub-images contain the occlusion, the online process starts with removing occlusion within sub-images. This occlusion removal

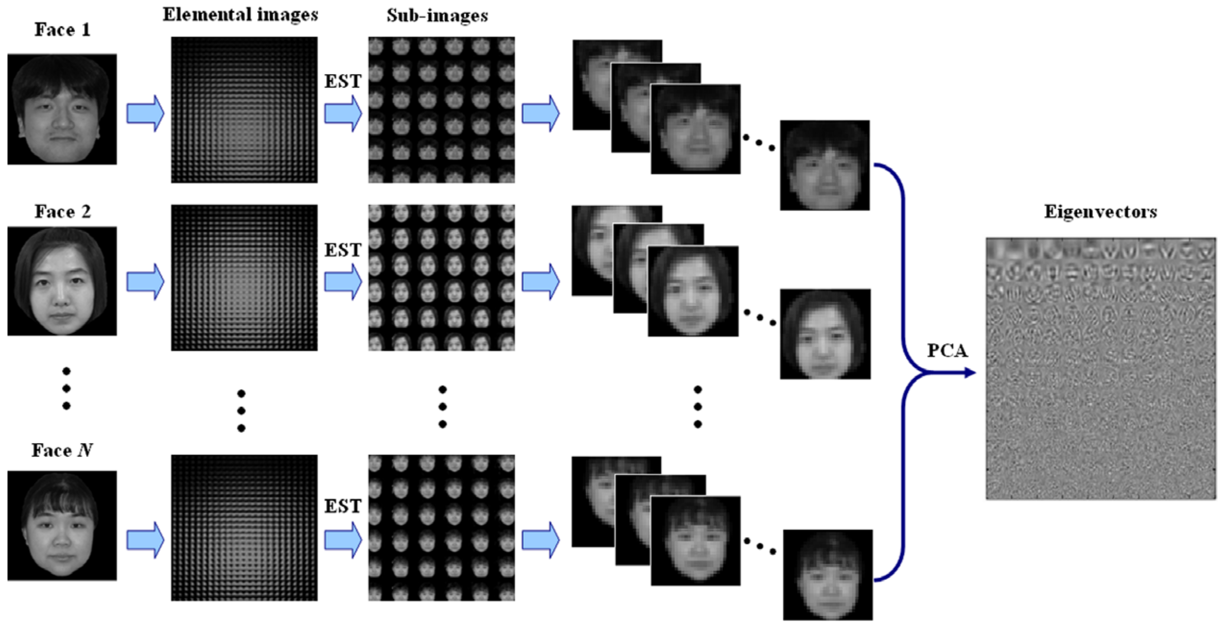

Fig. 3. Detail PCA training in the offline process.

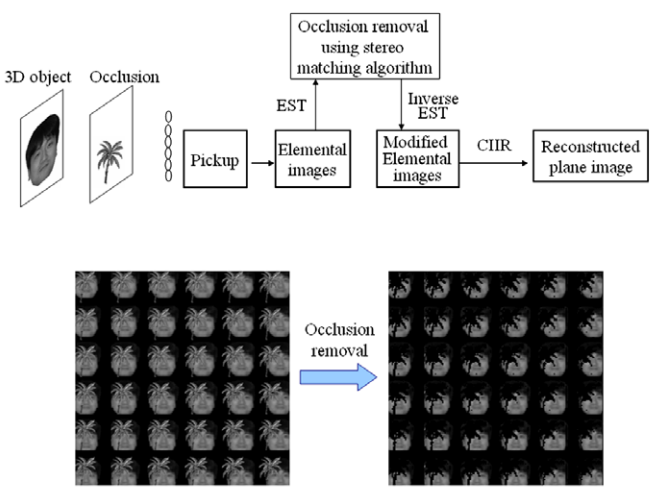

Fig. 4. Occlusion removal method in the CoII system.

method is shown in Fig. 4. To remove the unknown occlusion in the sub-images, we may use disparity information by the sub-image block matching algorithm, which is well known in the stereo vision [14]. After applying the sub-image block matching between two sub-images as shown in Fig. 4, 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-images without occlusion image as shown in Fig. 4.

In fact, the occlusion-removed elemental images cause the serious degradation in the performance of 3D object recognition because of losing some information of 3D object. To overcome this problem, in this paper, we restore the lost information using the eigenvectors generated in the previous offline process. The restoration process starts with making a reconstruction image of the occlusion-removed sub-image. This is given by

$$\hat{X}^j = m + \sum_{i=1}^{k} y_i^{j-1} u_i \tag{8}$$

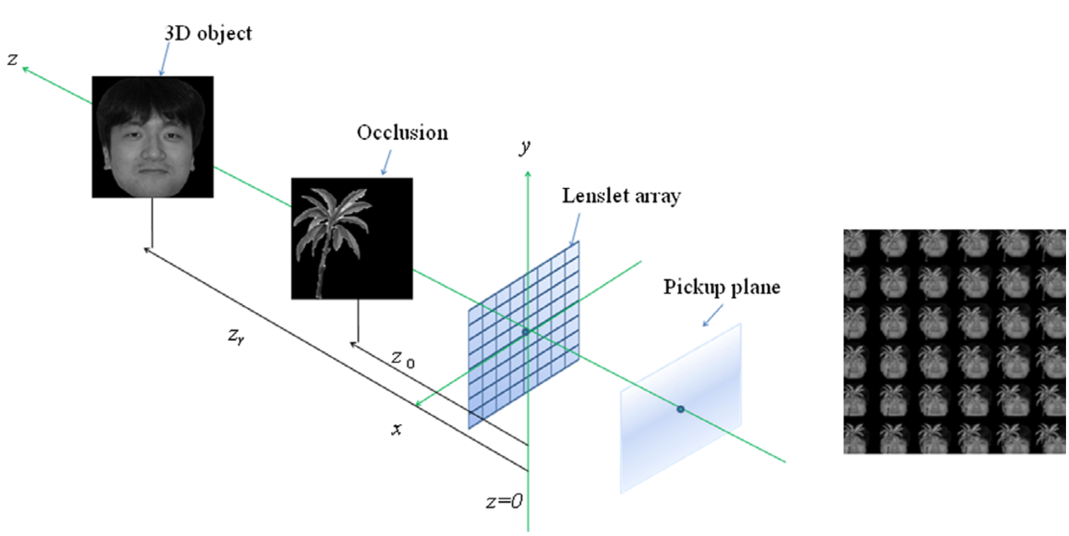

Fig. 5. Experimental structure.

Fig. 6. Ten faces for computational experiments.

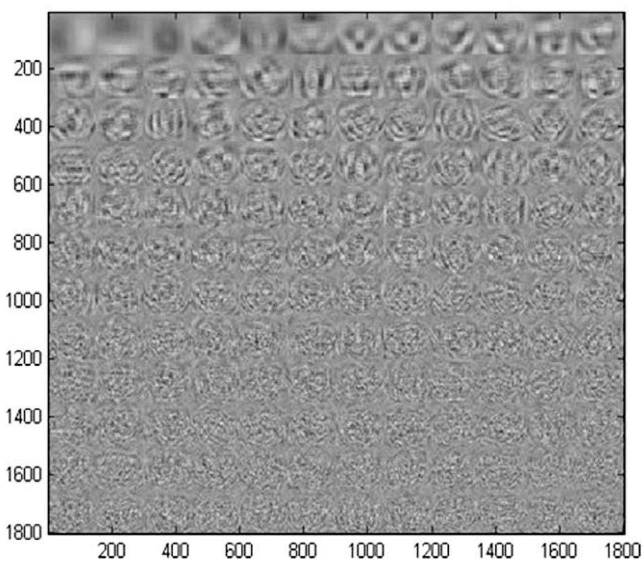

Fig. 7. Examples of eigenvectors produced from our offline process.

where $\hat{X}$ is the reconstructed sub-image from an input sub-image and the subscript 'j' is j-th iteration. k is the number of the eigenvectors and y is the projection coefficient onto each eigenvector which can be computed by Eq. (7). In the j-th recursive iteration, y is calculated by

$$y_i^j = u_i^T(X^j - m) \tag{9}$$

Using the original sub-image (X) and the reconstructed sub-image ($\hat{X}$), the restored sub-image can be obtained by using the Eq. (10), which is shown in

$$\bar{X}^j = w \cdot X + (1 - w) \cdot \hat{X}^j \tag{10}$$

Here, w is weight in range [0,1]. And w is a matrix contains '1' for every remaining pixel on the occlusion-removed sub-image and '0' for every eliminated pixel. This matrix means that it keeps the remaining part and replaces the missing part with the predicted sub-image. The location of missing pixels can be known using the depth map produced by the block matching process.

This recursive iteration stops if the difference between two successive coefficients (y_j and y_{j-1}) becomes less than a given threshold (ε). The D value can be calculated as given in

$$D = \max(|y_i^j - y_i^{j-1}|) < \varepsilon \tag{11}$$

As a result of recursive PCA reconstruction, the target sub-images without occlusion can be generated in the last iteration of the proposed system.

Next, with this modified target sub-images, we apply the reverse EST to it and we obtain the modified target elemental images. Based on the CIIR method, the target plane image is reconstructed at a specific distance. Finally, the cross correlation is done by comparing the reconstructed plane image of the target 3D object and the reference templates.

4. Computational experiments and results

To show the usefulness of the proposed technique, we performed computational experiments for face recognition, which has been regarded as a useful application of image restoration. The experimental structure is shown in Fig. 5. A pinhole array was used instead of a lenslet array for computational experiments. The target object to be recognized is the 'face' image. This is located at z_r = 45 mm. The 'tree' image is used as the unknown occluding object located at z_o = 18 mm from the pinhole array.

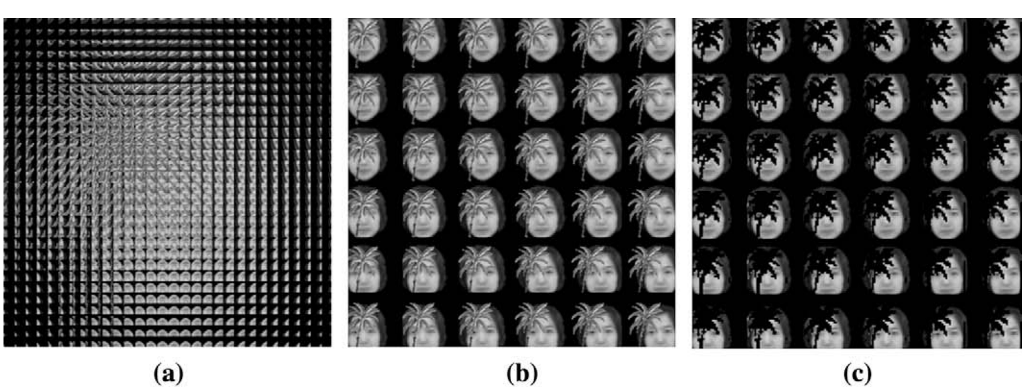

Fig. 8. (a) Captured elemental images (b) sub-images (c) occlusion-removed sub-images.

First, we simulated the offline process in the proposed system. The elemental images for target object are synthesized through a pinhole array in the reference CoII system. Here 10 faces are used as target object set as shown in Fig. 6. The pinhole array consists of 30×30 pinholes and the pinhole pitch is 1.08 mm. With this pinhole array, we obtained the elemental images with the resolution of 900×900 pixels. The synthesized elemental images were transformed into the corresponding sub-images. In the offline process, 10 faces' elemental images were transformed into 6×6 sub-images in order to obtain high-resolution sub-images for easy occlusion removal. Then, we took each sub-image as the reference training images as shown in Fig. 3. In this experiment, we used total 360 images as reference training images for 10 faces. Eigenvectors were calculated using the procedure of Fig. 3 and stored in a computer. The eigenvectors produced from our offline process are shown in Fig. 7. Although the offline process can produce maximal 360 eigenvectors, Fig. 7 shows 144 eigenvectors with high eigenvalue. This was arranged as 12×12 eigenvector images.

Next, in the online process as shown in Fig. 2b, the target elemental images including the target object 'face' and the occluding object 'tree' was captured. The captured target elemental images are shown in Fig. 8a. The target elemental images were transformed into the sub-images as shown in Fig. 8b. We applied the block matching as described in Fig. 4 to two images among sub-images and then obtained occlusion-removed sub-images as shown in Fig. 8c. As shown in Fig. 8c, the occlusion-removed sub-images have black regions where occlusion exits after eliminating it. This means that occlusion-removed elemental images have partially information loss because the pixels of black regions represented by occlusion become zero value in a gray level. In this paper, to minimize the information loss, we reconstructed compensated sub-images by using the recursive PCA method as described in Chapter 3.3. The iterations repeated until the difference between the compensated images and the previous images satisfied the threshold value. Examples of the compensated sub-images according to the iteration are shown in Fig. 9. From the results of Fig. 9, it is seen that the image quality of the reconstructed sub-images improved significantly as the iteration of the recursive PCA method increases.

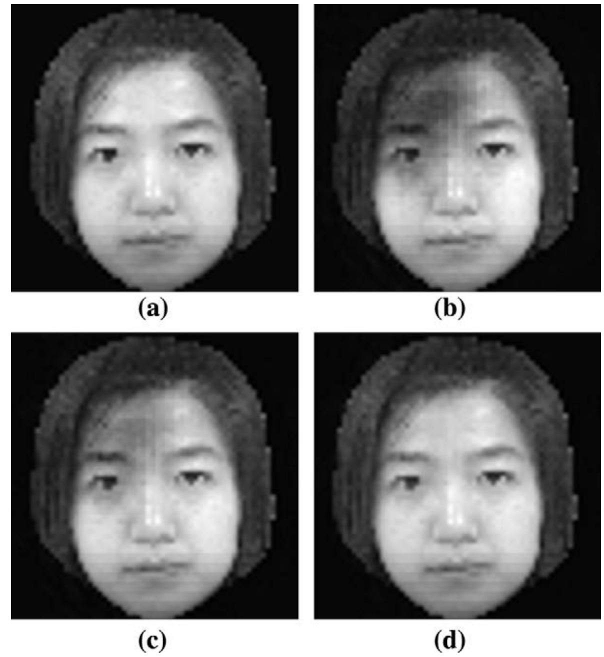

Fig. 10. Reconstructed plane images using CIIR method (a) original face image (b) 5-th iteration, (c) 10-th iteration, (d) 30-th iteration.

By using the reconstructed sub-images, the 3D object recognition experiments were performed. The sub-images were transformed into the modified elemental images using the reverse EST and the plane image was reconstructed at 45 mm by using CIIR method. Fig. 10 shows the reconstructed images of the proposed CoII system using the recursive PCA method. The originally recon-

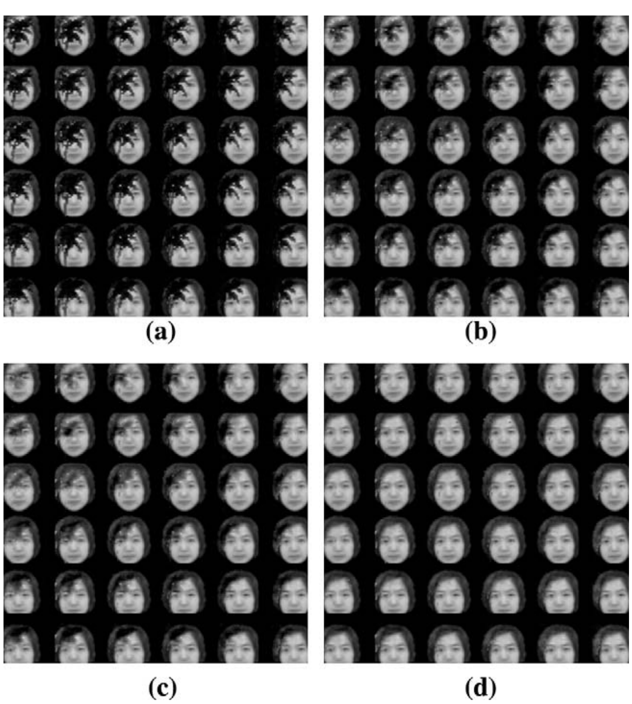

Fig. 9. Examples of compensated sub-images (a) 1-st iteration (b) 5-th iteration (c) 10-th iteration, (d) 30-th iterations.

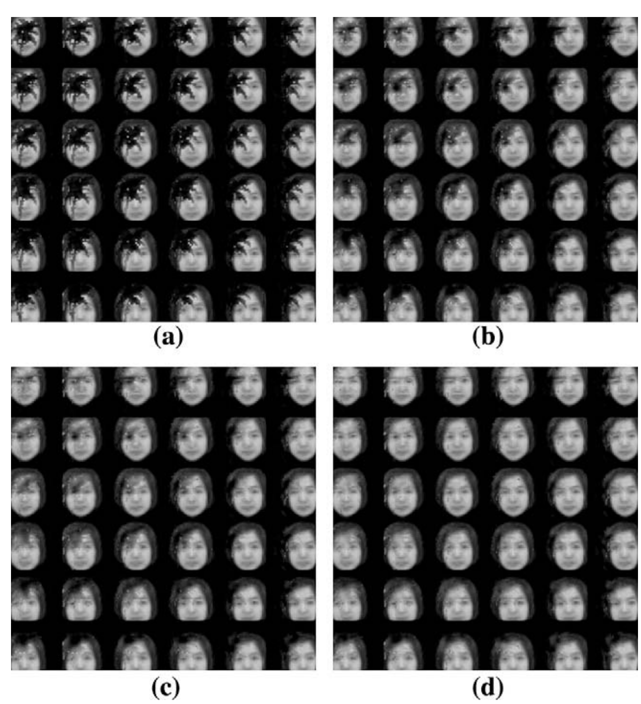

Fig. 11. Examples of compensated sub-images when $z = 51$ mm (a) 1-st iteration (b) 5-th iteration (c) 10-th iteration, (d) 30-th iterations.

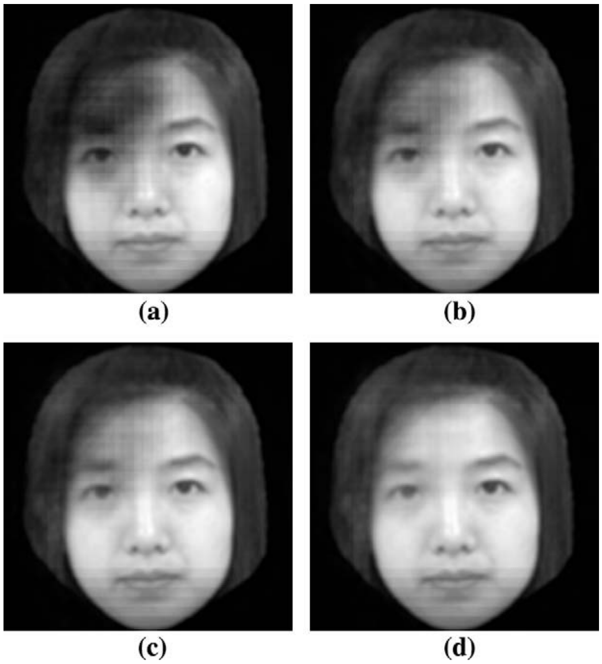

Fig. 12. Reconstructed plane images using CIIR method when $z = 51$ mm (a) 1-st iteration (b) 5-th iteration, (c) 10-th iteration, (d) 30-th iteration.

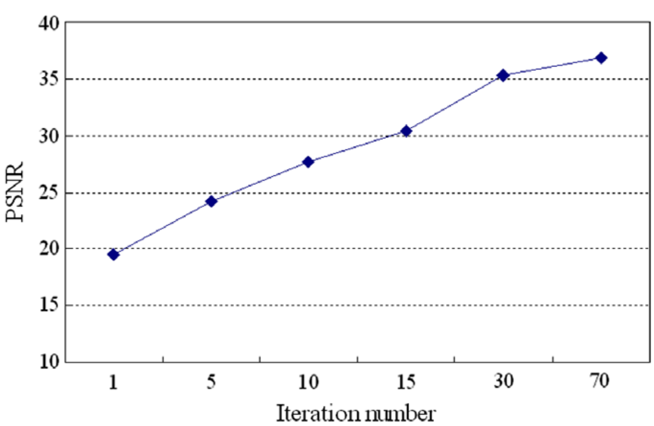

Fig. 13. Average PSNR results for reconstructed plane images.

structed plane image is shown in Fig. 10a. For comparison, the face image reconstructed in the conventional CoII system is shown in Fig. 10b. This is not clear and it has low contrast because of the blurring effect caused by the unknown occlusion. However, we can see that the high contrast images reconstructed from the proposed CoII system are obtained as shown in Fig. 10c and d. This may improve the correlation performance.

The additional experiments were performed to find the characteristics on the location of target object. The online process was repeated for various distance of target object. Among them, the compensated sub-images according to the iteration and reconstructed images when the target object is located at $z = 51$ mm were shown in Figs. 11 and 12, respectively. From these experiments, it is seen that it is possible to compensate elemental images regardless of the distance of target object. This is because the distance information of target object is transformed into shifting in sub-images [17] and these shifted sub-images are already trained in the offline process.

To objectively evaluate our experiments, we measured PSNR between the original image and the reconstructed one. PSNR is defined as

$$\mathrm{PSNR}(I_o, I_r) = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}(I_o, I_r)}\right) \tag{12}$$

where I_o is an original image; and I_r is the reconstructed image. And Mean Squared Error (MSE) is given by

$$\mathrm{MSE} = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=1}^{Y-1}[I_o(x,y) - I_r(x,y)]^2 \tag{13}$$

where x and y are the pixel coordinates of images having $X \times Y$ pixels. The calculated PSNR results are shown in Fig. 13. The average PSNR of 10 face images was calculated for the various reconstructed images according to the iteration number of recursive PCA method. When using the CIIR images reconstructed from the occlusion-contained elemental images as shown in Fig. 8b, the PSNR was averagely 19.46 dB. On the other hand, we obtained the high PSNR value of 36.81 dB after 70 iterations using the proposed method. It is seen that the proposed CoII system provides a substantial gain in terms of PSNR value or visual quality. This is due to eliminating occlusion by the proposed technique and recovering the loss by occlusion.

Finally, to show the improved performance of the proposed method for 3D object recognition, we reconstructed various plane images according to the iteration number and performed the cor-

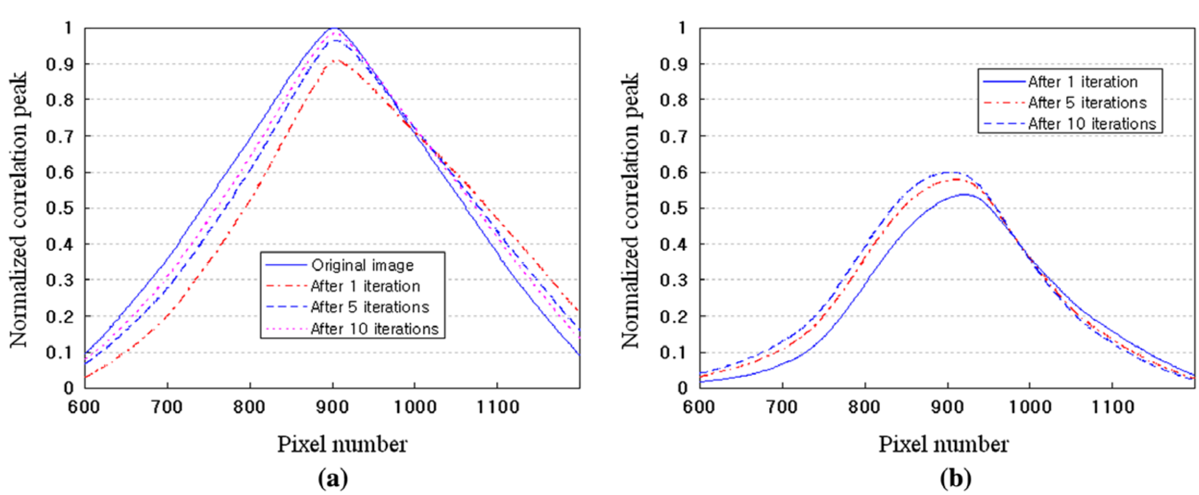

Fig. 14. Experimental results for image correlation (a) when the object is matched (b) when the object is not matched.

relation between an original image $I_o(x,y)$ and its reconstructed plane image $I_r(x,y)$. The correlation is defined as

$$C(x_c, y_c) = \frac{1}{uv}\sum_{x=1}^{u}\sum_{y=1}^{v}[I_r(x,y)I_o(x_c + x, y_c + y)]. \tag{14}$$

Using Eq. (14), we can calculate the correlation coefficients between $I_o(x,y)$ and $I_r(x,y)$. Fig. 14a shows the correlation results for 4 different images including original image and three reconstructed images as shown in Fig. 10a–c. For comparison, the correlation results when the object is not matched with the trained faces were shown in Fig. 14b. The results of Fig. 14 indicate that the correlation peak increases as the iteration number increases.

5. Conclusion

In conclusion, we have proposed a new CoII system based on a recursive PCA method for improved recognition of 3D objects that are occluded partially. We have introduced a recursive PCA method to eliminate occluding objects and recover the loss information in elemental images. This can provide a substantial gain in terms of the image quality of reconstructed plane image of 3D objects. To show the usefulness of the proposed technique, we represented some experiments for face recognition and demonstrated the improvement of recognition performance. Therefore, it is expected that the proposed system will aid to improve the performance of 3D object recognition.

Acknowledgement

This work was supported by research fund from Dongseo University, Dongseo Frontier Project Research Fund of 2009.

References

[1] G. Lippmann, C.R. Acad. Sci. 146 (1908) 446.
[2] A. Stern, B. Javidi, Proc. IEEE 94 (2006) 591.
[3] B. Lee, S.Y. Jung, S.-W. Min, J.-H. Park, Opt. Lett. 26 (2001) 1481.
[4] J.-S. Jang, B. Javidi, Opt. Lett. 27 (2002) 324.
[5] M. Martínez-Corral, B. Javidi, R. Martínez-Cuenca, G. Saavedra, J. Opt. Soc. Am. A 22 (2005) 597.
[6] D.-H. Shin, S.-H. Lee, E.-S. Kim, Opt. Commun. 275 (2007) 330.
[7] Y. Frauel, B. Javidi, Appl. Opt. 41 (2002) 5488.
[8] S.-H. Hong, J.-S. Jang, B. Javidi, Opt. Express 12 (2004) 483.
[9] B. Javidi, R. Ponce-Díaz, S.-H. Hong, Opt. Lett. 31 (2006) 1106.
[10] S.-H. Hong, B. Javidi, Opt. Express 14 (2006) 12085.
[11] D.-C. Hwang, J.-S. Park, D.-H. Shin, E.-S. Kim, Opt. Commun. 281 (2008) 5991.
[12] D.-H. Shin, H. Yoo, Opt. Express 16 (2008) 8855.
[13] D.-H. Shin, E.-S. Kim, J. Opt. Soc. Korea 12 (2008) 131.
[14] D.-H. Shin, B.-G. Lee, J.-J. Lee, Opt. Express 16 (2008) 16294.
[15] M. Turk, A. Pentland, J. Cognit. Neurosci. 3 (1991) 71.
[16] J.-S. Park, Y.-H. Oh, S.-C. Ahn, S.-W. Lee, IEEE Trans. Pattern Anal. Mach. Intell. 27 (2005) 805.
[17] J.-H. Park, J. Kim, B. Lee, Opt. Express 13 (2005) 5116.