3D Image Correlator using Computational Integral Imaging Reconstruction Based on Modified Convolution Property of Periodic Functions

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In this paper, we propose a three-dimensional (3D) image correlator by use of computational integral imaging reconstruction based on the modified convolution property of periodic functions (CPPF) for recognition of partially occluded objects. In the proposed correlator, elemental images of the reference and target objects are picked up by a lenslet array, and subsequently are transformed to a sub-image array which contains different perspectives according to the viewing direction. The modified version of the CPPF is applied to the sub-images. This enables us to produce the plane sub-image arrays without the magnification and superimposition processes used in the conventional methods. With the modified CPPF and the sub-image arrays, we reconstruct the reference and target plane sub-image arrays according to the reconstruction plane. 3D object recognition is performed through cross-correlations between the reference and the target plane sub-image arrays. To show the feasibility of the proposed method, some preliminary experiments on the target objects are carried out and the results are presented. Experimental results reveal that the use of plane sub-image arrays enables us to improve the correlation performance, compared to the conventional method using the computational integral imaging reconstruction algorithm.

Keywords: Integral imaging, 3D correlation, Elemental images, Lenslet array

OCIS codes: (110.0110) Imaging systems; (110.6880) Three-dimensional image acquisition

I. INTRODUCTION

Occluded objects have been an interesting research area for the field of three-dimensional (3D) object visualization and recognition. Recently, several approaches employed a 3D imaging technique to solve the occlusion problem [1-9]. Among them, integral imaging can be considered as one of the promising solutions, and thus some techniques-based on integral imaging have been proposed for 3D recognition of partially occluded objects. Integral imaging is a method of recording and displaying techniques for 3D scenes with the lenslet array. The recorded elemental images consist of several two-dimensional (2D) images with different perspectives [10-17]. In 2007, a 3D image correlator using the computational integral imaging reconstruction (CIIR) method was proposed [6]. In CIIR, the plane images were generated by the magnification and superimposition process of elemental images. Each plane image contains both focused and defocused images for occlusion and target objects. This enables us to recognize target objects with occlusion. However, the CIIR process may produce the addition of blur noises in plane images due to the interpolated images and high computation loads. To overcome this problem, the modified CIIR-based 3D correlator using smart pixel mapping, which can reduce the magnification factor and thus improve the correlation performance, was proposed in 2008 [7]. However, this method also utilized the magnification process to generate the depth-converted plane images.

Recently, a depth slicing method using a convolution property between periodic functions (CPPF) has been proposed to produce the plane image array, which is similar to plane images from the previous CIIR method [18, 19]. In integral imaging with the lenslet array, an elemental image has periodic property depending on object depth.

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This method takes advantage of the periodic property of spatial frequency of an elemental image. The CPPF is performed by convolution between the elemental image and the 2D \( \delta \)-function array whose spatial period corresponds with target depth. As a result, the targeting depth image can be reconstructed as the structure of the plane image arrays with fast calculation time compared with the previous CIIR method. In addition, CPPF technique can be applied to optical 3D refocusing display with the lenslet array [20]. Here, 3D objects with their own perspectives can be reconstructed to be refocused on their depth in the space for viewers.

In this paper, we propose a 3D image correlator using the computational reconstruction based on the modified CPPF for partially occluded object recognition. We introduce a modified CPPF (MCPPF) method for sub-images to produce the plane sub-image arrays (PSAs) without magnification and superimposition processes used in the conventional methods. In the proposed correlator, elemental images of the reference and target objects are captured by the image sensor through the lenslet array. And, the recorded elemental images are transformed to the sub-images, which contain different perspectives according to the viewing direction. The proposed MCPPF method can be applied to these sub-image arrays for reconstruction of the 3DPSAs. Only the target PSA is reconstructed on the right plane where the target object was originally located and contains clearly focused perspectives. On the other hand, other target PSAs are reconstructed on the various reconstruction planes where the focused and blurred images are mixed. 3D object recognition is performed through cross-correlations between the reference and the target PSAs. To show the feasibility of the proposed method, some preliminary experiments on the target objects are carried out and the results are presented.

II. PROPOSED MCPPF-BASED 3D IMAGE CORRELATOR

Figure 1 shows the schematic diagram of the proposed method. The proposed method is divided into four processes; (1) pickup, (2) sub-image transform, (3) computational reconstruction using MCPPF and (4) recognition processes.

2.1. Pickup Process

The first process of the proposed method is pickup of 3D objects. This is the same as the conventional pickup process.
process in integral imaging. The lenslet array is used to capture 3D objects. We assume that a reference object \(R(x, y, z)\) is located at the known distance of \(z\) in front of a lens array in the pickup system as shown in Fig. 1(a). And a target object \(O(x_0, y_0, z_0)\), to be recognized is partially occluded by the occlusion object and located at an arbitrary distance of \(z_o\) in front of the lenslet array. Then elemental images of the reference and target objects are recorded by the lenslet array and the 2D image sensor. The recorded elemental images of the reference and target objects are stored for the use of the next process.

The conventional pickup process of an integral imaging system by using the direct pickup method is based on ray optics. The geometrical relationship between a point object and its corresponding point images on the elemental image plane is shown in Fig. 2(a). In the conventional integral imaging system with planar lenslet array, the geometrical relation of 2D form is given by

\[
x_{E_k} = x_o + \frac{z_o}{z_o + f} \left( k - \frac{1}{2} P - x_o \right)
\]

In the Fig. 2(a) and Eq. (1), the origin of the coordinates is the edge of the elemental lens located at the bottom of the lenslet array. The object point \((x_o, y_o, z_o)\) is the position along the \(x\), \(y\), and \(z\) axes, respectively. \(P\) represents the distance between the optical centers of the neighboring elemental lenses and is assumed to be the same as the lateral length of an elemental image. \(f\) is the focal length of an elemental lens in a planar lenslet array. \(x_{E_k}\) and \(y_{E_k}\) are the image point by the \(k\)th and \(l\)th elemental lenses, respectively. The imaging distance of a point object measured from lenslet array is \(z_{E_k} = z_o / (z_o + f)\). \(X_{E_k}\) is depth-dependent spatial period. However, due to the limit of resolution of a pickup device, Eq. (1) should be converted into pixel units. Thus the pixelated version of Eq. (1) is denoted by

\[
x_{E_k} = \text{cell} \left[ x_{E_k} \times \frac{N}{P_{\text{max}}} \right],
\]

where \(N\), \(P\), and \(P_{\text{max}}\) are lateral resolution of the elemental image array in one-dimensional (1D) condition, the diameter of an elemental image and the lateral number of elemental lenses, respectively.

From the geometrical relationship, the 1D form of spatial period depending on object depth is given by \(|x_{E_k} - x_{E_{k-1}}|\), \(2 \leq i \leq P_{\text{max}}\). Then the depth dependent spatial period is to be \(|x_{E_k} - x_{E_{k-1}}| = z_o P / (z_o + f)|\). Hence, the pixelated version is denoted by

\[
X_{z_o} = |x_{E_k} - x_{E_{k-1}}|.
\]

Equation (3) implies that the intensity of the elemental image corresponding with an object locating specific depth is imaged with the same interval on the imaging plane as described in Fig. 2(b). Thus, a lenslet array in an integral imaging system may be regarded as the conveter which converts depth information of 3D space changes into 2D periodic information and vice versa.

### 2.2. Sub-image Transform

The recorded elemental images do not have the characteristic of the shift invariance. That is, the projected small images in elemental images are scale-changed if the 3D object is located at different locations. For this reason, we apply the sub-image transform to the recorded elemental images. The sub-image array can provide both shift invariance and the whole projected image in elemental images [5]. The sub-image transform can be performed based on either single pixel extraction or multiple-pixel extraction. In this paper, our intention is to apply the concept of conventional CPPF to sub-images for the proposed 3D image correlator. Therefore, the conventional CPPF technique can be modified for sub-images.

We explain the principle of the proposed MCPPF method for sub-image array. The lateral resolution of the elemental image array \(N\) is given by \(N = n \times k_{\text{max}}\) when an elemental image is composed of \(n\) pixels. The \(x_{E_{k_{\max}}}\) may be represented as ordered pair \((k, m)\), where \(k\) is index of an elemental image and \(m\) is given by \(m = x_{E_{k_{\max}}} - (k - 1) n\). \(m\) is order of pixel in \(k\)th elemental image and \(1 \leq m \leq n\). The lateral resolution of sub-image array is the same as that of the elemental image array, \(N\). If the number of sub-image array is \(f_{\text{max}}\) and each sub-image is composed of \(\xi\) pixels, then the \(N\) can be described by \(N = \xi \times j_{\text{max}}\). A pixel in the sub-image array may be also represented as ordered pair \((j, \eta)\), where \(j\) is a sub-image number and \(\eta\) is order of the pixel in \(j\) th sub-image and \(1 \leq \eta \leq \xi\). In this variable correspondence, we can find the relationship as follows

\[
\xi = c k_{\text{max}},
\]

where \(c\) is the number of pixels to be extracted for sub-image transform.

To show the periodic property of sub-image array adequately, let us consider the condition \(c = 1\) as shown in Fig. 3. The pixel correspondence between elemental image array and sub-image array may be represented as follows

\[
(k, m) \to_{\text{sub}} (j, \eta) = (m, k).
\]
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sub-image array and a \( \delta \)-function array. The pixel extraction factor in Eq. (4) is applied by \( c=5 \). The resolution of a sub-image is 150×150 pixels. The \( X_{sub} \) is spatial period of \( \delta \)-function array, and the spatial period varies depending on target depth. The images arranged in the middle of Fig. 4 are output results of the MCPPF according to spatial period with 1 pixel interval. To observe the results clearly, the enlarged images are prepared at the bottom of Fig. 4.

### 2.4. Recognition Process

From the process of computational reconstruction based on MCPPF, we can reconstruct the reference and target PSAs. First, the reference PSA is reconstructed on the known \( z_r \)-plane for the reference object. This is called the reference template. Next, for the partially occluded target object, a set of target PSAs are reconstructed on each reconstruction plane by changing the distance \( z \) from the lenslet array as shown in Fig. 1(c). Among them, the target PSA reconstructed at the \( z_o \)-plane of the original position of the target object during the pickup process has highly focused images of the target object. On the other hand, the other target PSAs reconstructed on the \( z \)-planes far away from the \( z_o \)-plane become out of focus.

Once a target PSA \( P_o(x, y, z) \) of the target object reconstructed at the arbitrary distance of \( z \) using the MCPPF technique is generated, the correlation process can be performed between the target PSA of \( P_o(x, y, z) \) and the reference template of \( P_R(x, y, z) \). Accordingly, we calculate the correlation result using the following correlation operation as given by

\[
C(x, y, z) = \frac{1}{W \times H} \sum_{x'=1}^{W} \sum_{y'=1}^{H} [P_o^*(x', y', z) \odot P_o(x + x', y + y', z)]
\]

where * denotes the complex conjugate. It is seen that the correlation peak \( C(z) \) is a function of distance \( z \) and the behavior of \( C(z) \) such as sharpness can be a performance measure for 3D object recognition. This correlation process is repeated for all target PSAs reconstructed on \( z \)-planes by varying the distance \( z \) within the desired depth range. In fact, since the target PSA with the most highly focused target image is reconstructed at the \( z_o \)-plane, a sharp correlation peak may be expected to be occurred on the \( z_o \)-plane through the correlations between the known reference template and target PSAs of the target object.

### III. EXPERIMENTAL RESULTS AND DISCUSSIONS

To demonstrate the feasibility of our proposed 3D image correlator, the preliminary experiment on the 3D objects in space was performed. In the experiment, a 3D object (car) is employed as reference test object as illustrated in Fig. 5(a). And, the occlusion (a bundle of plants) is shown in Fig. 5(b). Figure 5(c) shows the camera view image as the object and the occlusion are arranged in the object field.

The experimental structure is shown in Fig. 6. The 3D object and occlusion are located at 200 mm and 100 mm...
from the lenslet array, respectively. Here the lenslet array is composed of 30×30 lenslets, and the lenslet diameter and the focal length are 5 mm and 15 mm, respectively.

Using the experimental setup of Fig. 6, we first recorded the elemental images of reference objects which were located at a known position \( z = 200 \) mm in front of a lenslet array. And, we captured the elemental image array of the unknown target object, which was located at an arbitrary position behind occlusion. Figure 7(a) and (b) show the captured elemental images for reference object and partially occluded object, respectively. And the corresponding sub-images are shown in Fig. 7(c) and (d) after sub-image transform. The resolutions of the elemental images and sub-images are 900×900 pixels.

Figure 8(a) shows the reconstructed PSA of reference object using the computational reconstruction based on MCPPF for sub-images of Fig. 7(c), which the reconstruction depth was 200 mm. Using the sub-images of the partially occluded object shown in Fig. 7(d), we generated their target PSAs according to the distances from 170 mm to 230 mm with the step of 5 mm. Some examples are shown in Fig. 8(b).

With the reference PSA and target PSAs, the correlation performances of the proposed method were measured using the correlation operation of Eq. (9). Correlation results were calculated by conducting the correlation between the reference PSA and a series of the target PSAs. The correlation results are shown in Figs. 9 and 10. Figure 9 shows the auto-correlation results of the reference object shown in Fig. 5(a). The correlation array was obtained due to the image array structure of PSAs. Among them, the maximum correlation peak was measured for object recognition. The curve of correlation peaks from the proposed method along the distance \( z \) was shown in Fig. 9(b). This result indicates that the ‘car’ object is located at \( z = 200 \) mm because the maximum of correlation peaks is obtained at this distance.

And the correlation result for the partially occluded object between the proposed and conventional methods.
objects as shown in Fig. 5(c) was shown in Fig. 10(a). The curve of maximum correlation peaks for two different cars (True car and False car) were calculated and presented in Fig. 10(b).

In addition, we compared the proposed method with the conventional method based on CIIR [7]. The comparison experiments were performed under the same condition. The recorded elemental images were used to generate the CIIR images. The CIIR images for the reference object and the unknown target object were shown in Fig. 11. We compared correlation peaks of partially occluded object between proposed and conventional methods as shown in Fig. 12. Each correlation peak was normalized using the value of the maximum correlation peak obtained in the proposed method. For the conventional method, the maximum value of correlation peak was approximately 0.94. It is seen that the proposed method provides not only higher correlation peak but also sharper characteristic of correlation peaks than the conventional method. This is because our method can remove the blurring effect due to the magnification and superimposing processes of the CIIR process.

IV. CONCLUSIONS

In conclusion, we proposed a new 3D image correlator using the computational reconstruction based on MCPPF for partially occluded object recognition. In the proposed correlator, PSAs generated from MCPPF were used for 3D object recognition and thus we can recognize the partially occluded 3D object using the maximum peaks correlated with the reference object. Some preliminary experiments show the usefulness of the proposed method by comparison with the conventional method using CIIR.

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