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Improving Depth Measurement of Textured Surface by a Boundary Estimator for Structured Light Patterns

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***Abstract*— In home service robot applications, robots often deal with textured objects. The variation of surface's reflectivity may decrease the accuracy of depth measurement of structured light 3D camera. In this paper, we propose a new method to correct the boundary of structured light pattern in order to increase the accuracy of depth measurement. The algorithm first estimates the reflection index of the surface. The light stripe is deconvoluted to remove the smooth effect of the camera lens. Finally, the edge is normalised by the reflection index, and the boundary is estimated from the intersection between the corrected versions of the edge and its inverse. The experimental results show that with the proposed boundary estimator, there are significant improvements in term of surface smoothness of textured objects.**

I. Introduction

The advantages of structured light 3D cameras are that they can provide very accurate 3D point clouds of the objects especially with textureless objects, and are robust to the lighting conditions. Thus they are widely used in home service robot applications such as object recognition and pose estimation. However, the objects in the home environment usually have textures, which cause reflectance discontinuities on the surface of the object. That is one of the major sources of errors for 3D imaging system based on structured light. The crucial step for accuracy of depth image is the estimation of the boundary of the light stripes, which classifies pixels from the captured image to the white or black stripe.

On the textureless object, since the light stripe is only affected by the Gaussian blur effect (Fig. 1(a)), the boundary of the stripe can be detected with sub-pixel accuracy. However, on the textured object, except for the blur effect the light stripe is also deformed because of the reflectance discontinuities on the object surface, as illustrated in Fig. 1(b).

Though many structured light codes (patterns) have been proposed [1][2], but a few methods about boundary estimation for structured light patterns are introduced. There are two commonly used methods to find the boundaries of the light stripes, which were described in details by Trobina [3]:

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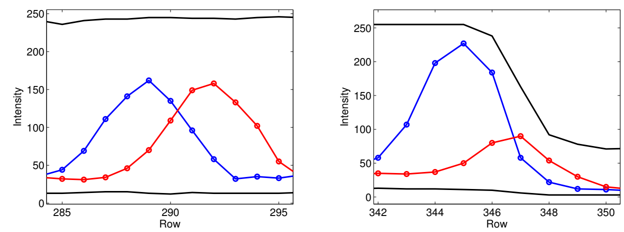
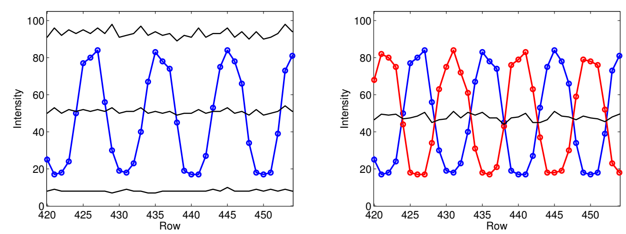


(a) (b)

Fig. 1. Different shapes of light stripe in the captured image.



(a) (b)

Fig. 2. Two boundary estimation methods. (a) project the reference images and use the average value as the threshold, (b) project the additional inverse pattern images, and use the zero-crossing value as the threshold.

- project the reference images (all white and all black) and use the average value as the threshold, or
- project the additional inverse pattern and use the zero-crossing value as the threshold.

These methods are illustrated in Fig. 2. The second method is more robust and reliable than the first one, since the intensity of the white image obtained by the camera cannot represent the white stripe in each frame. However, it turns out that these conventional methods are not suitable for estimating the boundary of the light stripes on the textured objects, because of the deformation of the light stripe's edge as mentioned above.

In this paper, we propose a method to correct the boundary in the case that the objects have textures causing the reflectance discontinuities on the surface. First the reflection index is estimated from the reference data when the projector illuminates all white and all black patterns. Then the deconvolution is applied to light stripe's edge. Finally, the edge is normalised by the reflection index, and the boundary is estimated from the intersection of the corrected versions of the edge and its inverse.

The remainder of the paper is organised as follows: In Section II, we describe our boundary correction method.

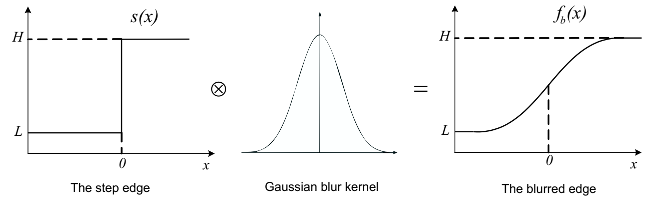


Fig. 3. The blurred edge is the result of the convolution of step function and Gaussian blur kernel.

The experimental results are provided in Section III. Finally, Section IV concludes the paper.

II. The Proposed Boundary Estimator

Since the CODEC patterns are defined by a periodic arrangement with a well defined orientation, we simply analyse the edge along one axis of orientation.

A. The Model of the Captured Structured Light Pattern

In structured light system, the patterns for illuminating often contain black and white stripes, with the edge is a step function:

$$s(x) = \begin{cases} H & x \geq 0 \\ L & x < 0 \end{cases}$$

The pattern which is blurred after passing through the projector lens is modeled by the convolution of a step function and a Gaussian blur kernel (as shown in Fig. 3):

$$f_b(x) = s(x) \otimes g_p(x, \sigma_p)$$

where $\otimes$ is the convolution operator, and the Gaussian blur kernel is a normalised Gaussian function

$$g_p(x, \sigma_p) = \frac{1}{\sigma_p\sqrt{2\pi}} e^{\left(-\frac{x^2}{2\sigma_p^2}\right)}$$

When the pattern is projected on a surface, the intensity of reflected light is changed depending on the reflection index of that surface. By denoting $R(x)$ as the reflection index of the surface at position x, we have

$$0 \leq R(x) \leq 1$$

When the projector illuminates a pattern on the object, the reflected amount is:

$$f_r(x) = f_b(x) * R(x) = (s(x) \otimes g_p(x, \sigma_p))\, R(x) \qquad (1)$$

where $*$ is the multiplication operator.

The input to the camera is the incoming light, which consists of two portions, as illustrated in Fig. 4:

1) The reflected amount of projector pattern, and
2) The ambient light $A(x)$.

And they are blurred once more by camera lens, which is modeled by a convolution with Gaussian blur kernel. Thus the captured data of the camera is:

$$f_c(x) = (f_r(x) + A(x)) \otimes g_c(x, \sigma_c) + W(x) \qquad (2)$$

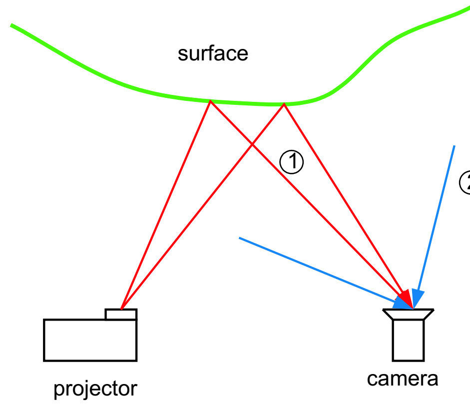


Fig. 4. The camera captures two portions: (1) projector pattern, and (2) ambient light.

where $W(x)$ is additive white Gaussian noise from camera sensor. And the Gaussian blur kernel of the camera lens is:

$$g_c(x, \sigma_c) = \frac{1}{\sigma_c\sqrt{2\pi}} e^{\left(-\frac{x^2}{2\sigma_c^2}\right)}$$

Substitute (1) in to (2) we have

$$\begin{aligned} f_c(x) = {} & ((s(x) \otimes g_p(x, \sigma_p))\, R(x) + A(x)) \otimes g_c(x, \sigma_c) \\ & + W(x) \end{aligned} \qquad (3)$$

Equation (3) is the one dimensional model of the structured light pattern in the captured image.

B. Correcting the Captured Pattern's Boundary Using Deconvolution

From the model of the captured pattern above, the wrong detected boundary using intersection method is caused by the dramatic change of the reflection index $R(x)$ and the Gaussian blur of the camera lens. That means to recover the correct boundary, the convolution $g_c(x, \sigma_c)$ and $R(x)$ need to be removed. The Richardson-Lucy deconvolution algorithm [4][5] can be used to remove the convolution $g_c(x, \sigma_c)$, in which the blur radius σ_c is estimated from the reference data by a curve fitting based blur estimation method. Then we can eliminate $R(x)$ by taking advantages of the reference data.

The mathematic expressions are as follows: we project and capture the three following patterns:

1) Reference data: $state1$ - the pattern is all white (or high intensity):

$$\begin{aligned} s_1(x) &= H \\ \Rightarrow f_1(x) &= (H * R(x) + A(x)) \otimes g(x, \sigma_c) + W_1(x) \end{aligned}$$

2) Reference data: $state0$ - the pattern is all black (or low intensity):

$$\begin{aligned} s_0(x) &= L \\ \Rightarrow f_0(x) &= (L * R(x) + A(x)) \otimes g(x, \sigma_c) + W_0(x) \end{aligned}$$

3) Pattern data: the pattern contains black and white stripes:

$$
\begin{aligned}
s_s(x) &= \begin{cases} H & x \geq 0 \\ L & x < 0 \end{cases} \\
\Rightarrow f_s(x) &= ((s(x) \otimes g_p(x, \sigma_p))R(x) \\
&\quad + A(x)) \otimes g_c(x, \sigma_c) + W_s(x)
\end{aligned}
$$

We subtract the captured reference data $state1$ by $state0$:

$$f_1(x) - f_0(x) = ((H - L)R(x)) \otimes g(x, \sigma_c) + (W_1(x) - W_0(x))$$

The Gaussian white noise $W_1(x)$ and $W_0(x)$ are different, but we assume that the subtraction $(W_1(x) - W_0(x))$ is small compared with reflected light intensity, so that we can approximate as:

$$f_1(x) - f_0(x) \approx ((H - L)R(x)) \otimes g(x, \sigma_c) \tag{4}$$

We use $(f_1(x) - f_0(x))$ to estimate the blur radius σ_c by using the curve fitting based blur estimation method. Then the reflection index will be computed from (4):

$$R(x) \approx \frac{deconvlucy\left((f_1(x) - f_0(x)), \sigma_c\right)}{H - L} \tag{5}$$

where $deconvlucy$ is the Richardson-Lucy deconvolution operator.

Now we compute the incident light, which is the amount of light from the projector hitting the surface $IncL(x) = (S(x) \otimes g(x, \sigma_p) - L)$:

The captured pattern data is:

$$
\begin{aligned}
f_s(x) &= \left[(S(x) \otimes g(x, \sigma_p))\, R(x) + A(x)\right] \otimes \\
&\quad g(x, \sigma_c) + W_s(x)
\end{aligned}
$$

The captured pattern data is subtracted by reference data:

$$
\begin{aligned}
f_s(x) - f_0(x) &= \left[(S(x) \otimes g(x, \sigma_p) - L)\, R(x)\right] \otimes \\
&\quad g(x, \sigma_c) + (W_s(x) - W_0(x))
\end{aligned}
$$

We can approximate as:

$$
\begin{aligned}
f_s(x) - f_0(x) &\approx \left[(S(x) \otimes g(x, \sigma_p) - L)\, R(x)\right] \otimes \\
&\quad g(x, \sigma_c)
\end{aligned}
$$

Thus the incident light is:

$$
\begin{aligned}
IncL(x) &= (S(x) \otimes g(x, \sigma_p) - L) \\
&\approx \frac{deconvlucy\left((f_s(x) - f_0(x)), \sigma_c\right)}{R(x)}
\end{aligned}
$$

With $R(x)$ from (5) we have:

$$IncL(x) \approx \frac{deconvlucy\left((f_s(x) - f_0(x)), \sigma_c\right)}{deconvlucy\left((f_1(x) - f_0(x)), \sigma_c\right)} (H - L) \tag{6}$$

In the case that the stripe's edge is affected by reflection index, the incident light $IncL(x)$ is computed using (6).

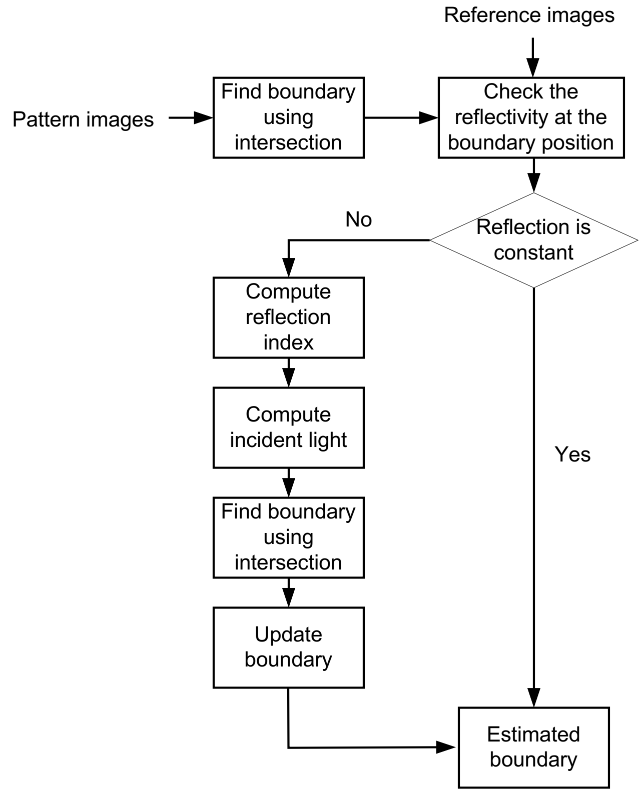


Fig. 5. The block diagram for the boundary estimator.

C. Boundary Estimator for Captured Pattern

The change of reflectivity of the object surface only affect on the pattern's edge when it has the same orientation with the edge. Moreover, the CODEC patterns of the structured light system is defined by a periodic arrangement with a well defined orientation, we can run the search along the row (if vertical pattern) or column (if horizontal pattern) of the captured image. The block diagram of the proposed boundary estimator is described in Fig. 5. In this diagram, the process "*Find boundary using intersection*" employs the method of projecting the additional inverse pattern and use the zero-crossing value as the threshold [3].

In order to check the reflectivity of the surface, the reference data: $state1$ and $state0$ (as formulated in Section B) are used:

$$
\begin{aligned}
f_1(x) - f_0(x) &= ((H - L)R(x)) \otimes g(x, \sigma_c) \\
&\quad + (W_1(x) - W_0(x)) \\
&\approx ((H - L)R(x)) \otimes g(x, \sigma_c)
\end{aligned}
$$

- If $R(x) = R$: reflection index is a constant:
  From a property of the convolution: the convolution of a normalised Gaussian function with a constant A is A. We have:

$$
\begin{aligned}
f_1(x) - f_0(x) &\approx ((H - L)R) \otimes g(x, \sigma_c) \\
&= (H - L)R \\
&= constant
\end{aligned}
$$

Thus the first derivative is:

$$\frac{\partial\left(f_1(x)-f_0(x)\right)}{\partial x}=0 \tag{7}$$

- If R(x) is not a constant: the absolute of the first derivative is:

$$\left|\frac{\partial\left(f_1(x)-f_0(x)\right)}{\partial x}\right|=\left|\frac{\partial\left(((H-L)R(x))\otimes g(x,\sigma_c)\right)}{\partial x}\right| \\ \neq constant \tag{8}$$

These properties (7) and (8) help us check the reflectivity of the surface. The reflection index is computed using (5) and the incident light is computed using (6).

III. Experimental Results

A. Experimental setting

For our experiments, we used a Canon projector and a PGR flea2 IEEE 1394 digital camera. The resolution of the projector was 1024x768 and the camera was 640x480. The position of the camera was about 30cm on the right of the projector. The distance between the system and the objects was about one meter. The original Hierarchical Orthogonal Code (HOC [6]) and the HOC with boundary correction version (HOC-B) were implemented and evaluated.

B. Results

The system was calibrated by using a calibration block with a coordinate was attached on it as shown in Fig. 6(a), thus two front faces of the calibration block have the plane equation $X = 0$ (left face) and $Y = 0$ (right face) respectively. We also reconstructed 3D data of this calibration block to evaluate the HOC and HOC-B, because it has flat faces which are easy for quantitative evaluations.

Fig. 6(a) shows pattern of the layer 4 of HOC on the calibration block. The estimated boundaries of four patterns with boundary correction are shown in Fig. 6(b), and without boundary correction in Fig. 6(c). Since the faces of the calibration block are flat, theoretically the detected boundaries of light stripes should be straight lines. But the variant of the surface reflection that deforms the edge of the pattern's stripe, thus the detected boundaries using conventional method are not on straight lines. As can be seen, the proposed method gives better estimation of the boundaries than the conventional method.

Fig. 7 illustrates the reconstructed 3D point clouds in various views of the calibration block using the HOC-B version on the left and the original HOC version on the right. And Fig. 8 shows the horizontal section of the 3D point cloud of HOC-B (Fig. 8(a)) and HOC (Fig. 8(b)). Obviously, without boundary correction, the 3D point of the surface has much variation at the boundary of black and white squares. Table I shows the quantitative measurement of the error of the reconstructed 3D data. The error was defined as the distance between the reconstructed point to the corresponding plane (left plane: $X = 0$ or right plane: $Y = 0$). As can be seen, mean and variance of the error were

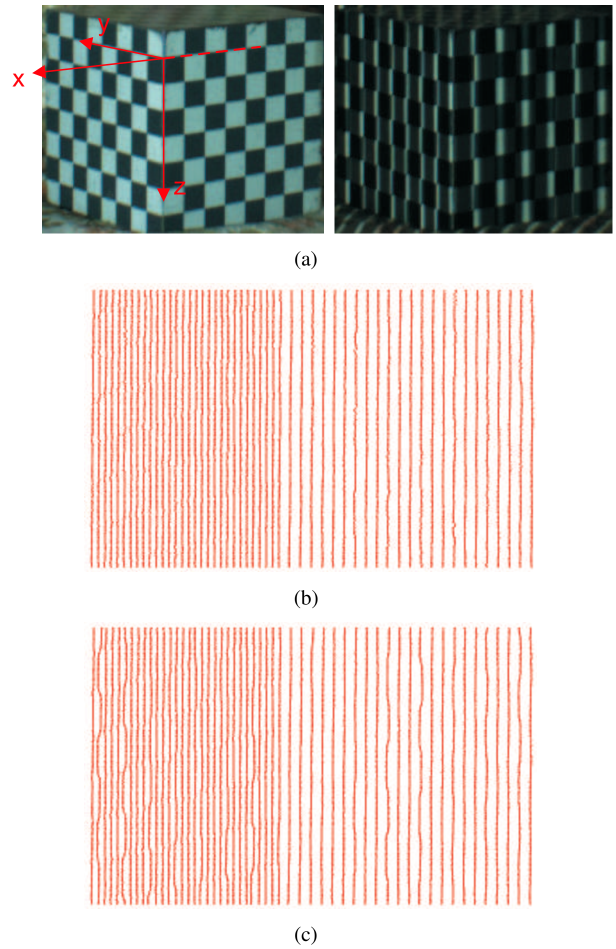


Fig. 6. The calibration block with structured light pattern (a). The detected boundary of light stripes using proposed method (b) and the conventional method (c).

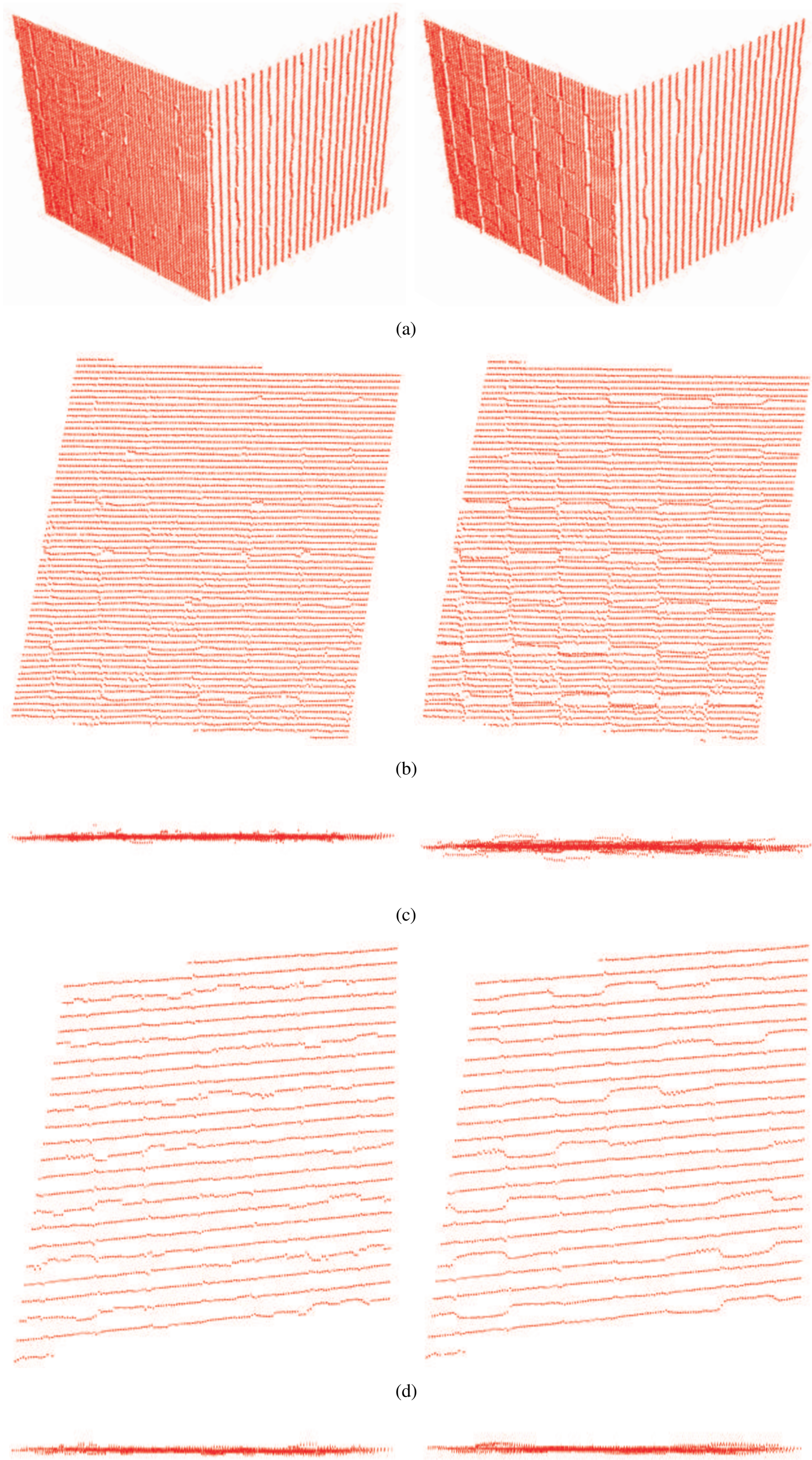
TABLE I
The Errors of Reconstructed 3D Data Using HOC and HOC-B

	Plane $X = 0$		Plane $Y = 0$	
	Mean of error (mm)	Variance of error (mm^2)	Mean of error (mm)	Variance of error (mm^2)
HOC-B	0.16094	0.027493	0.13298	0.017696
HOC	0.28607	0.15288	0.14389	0.022653

decreased when the boundary correction was applied to the HOC. Fig. 9 shows more examples about the improvements of HOC-B over HOC in the reconstructed 3D data of the textured objects.

IV. Conclusions

We have presented a method to correct the boundary of structured light pattern on a textured object in order to improve the accuracy of the depth measurement. The method bases on the estimation of the surface reflection index and the deconvolution of the pattern's edge. In this paper, the proposed boundary estimator is implemented on HOC, but it also can be applied to other structured light codes, such as Gray code, Binary code, etc.



(a)

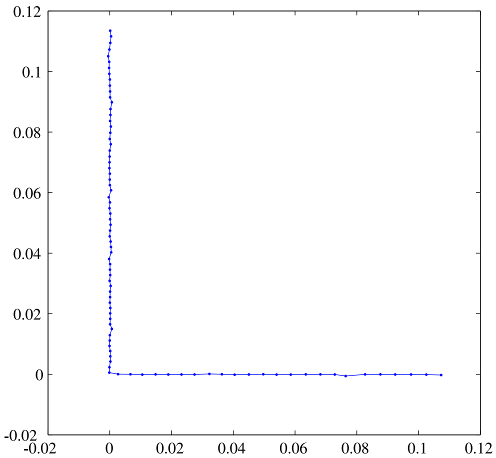
(b)

(c)

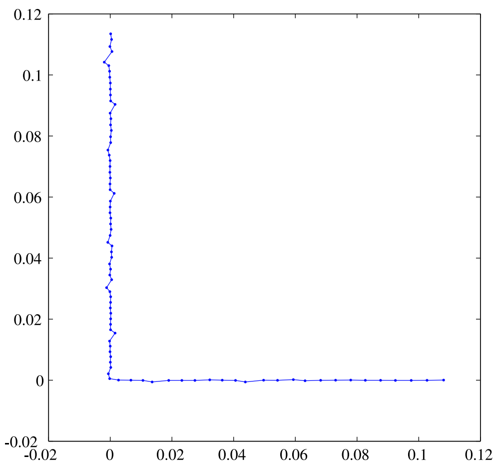
(d)

(e)

Fig. 7. The 3D point clouds of the calibration block using HOC-B (left) and HOC (right) in different views: (a) full view of visible faces; front view (b) and top view (c) of left face (plane $X = 0$); and front view (d) and top view (e) of right face (plane $Y = 0$).



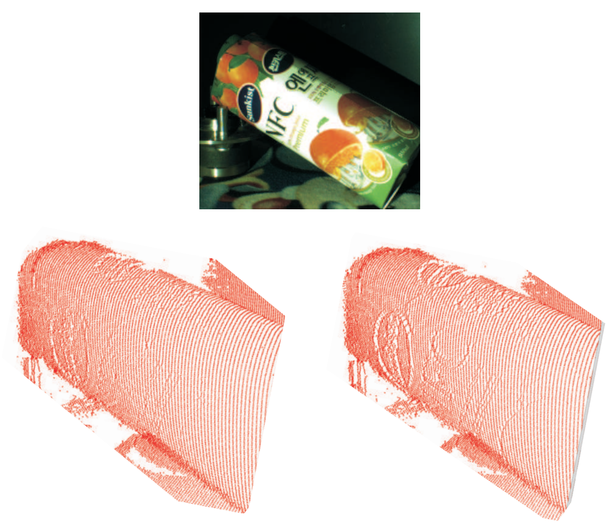
(a)



(b)

Fig. 8. The horizontal section of the 3D points of the calibration block. The 3D points are reconstructed using the HOC-B version (a) and with the original HOC version (b).

(a)



(b)

Fig. 9. The reconstructed 3D data of textures objects using HOC-B (left) and HOC (right): a cup (a) and an orange juice box (b).

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