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Light Pattern Blur Estimation for Automatic Projector Focus Control of Structured Light 3D Camera

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Abstract— **This paper presents a method of light pattern blur estimation for its application to automatic projector focus control in structured light 3D camera. To overcome shortcoming of the conventional methods for estimating blur of light pattern, we propose to normalise the light pattern image incorporating reference images. Which are made available by a structured light 3D camera. The reference black and white patterns are utilised in such a way as to eliminate the dependence of intensity variation around an edge on surface reflectivity. Then the unknown blur radius is estimated from the first derivative of normalised edge. Experimental results on both synthetic and real images verify that the proposed method is indeed independent of surface reflectivity and is accurate and sensitive enough to the small change of blur. Finally, based on the proposed light pattern blur estimation, a structured light 3D camera that is equipped with automatic multi-stage focus control in a beam projector has been built to demonstrate its capability of capturing the 3D workspace of large depth variations.**

I. INTRODUCTION

Depth imaging based on the structured light [1][2][3] has been drawn much attention in robotics applications because of its effectiveness not only over texture-less environments but also to various types of surface and lighting conditions. When using a structured light 3D camera, the limited depth of field (DOF) of a beam projector dictates the narrow range of measurable depths given a fixed projector focus. This is problematic in certain robotic applications when a fixed projector focus is used for a structured light 3D camera, since the robots may operate in the workspace with large depth variations. One way to solve this problem is to endow a structured light 3D camera with the capability of automatic projector focus control. Unfortunately, no such focus control has been implemented to date. To implement an automatic projector focus control algorithm, we must first solve the problem of the blur estimation of the pattern projected onto the surface of the object.

Several blur estimation methods have been proposed: Chiang [4] computes the blur radius based on the blurred model using its first and third derivatives; Elder [5] proposes to use the second Gaussian derivative operator in estimation; Hu [6] first re-blurred the input edge twice with different blur radii, then the unknown blur radius is estimated from the difference ratios between the multiple re-blurred edges and the input edge; Price [7] uses a parametric blur model in conjunction with the maximum likelihood technique to estimate the blur function; and Rooms [8] proposes a wavelet based method to estimate the blur. However, it turns out that these conventional blur estimation methods are not suitable for estimating the blur of projector's light patterns of the structured light 3D camera: First, they are often erroneous and even in failure due to the variation of surface reflectivity. Second, they are not sensitive enough to the small change of blur.

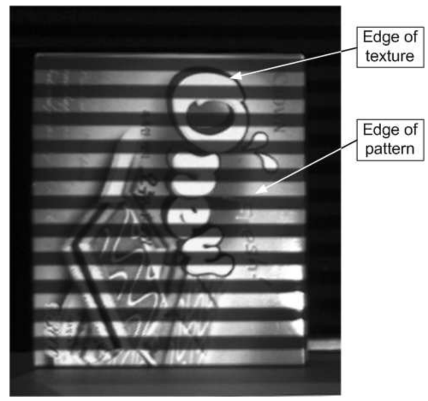

Fig. 1. Illustrative object with edges of texture and light pattern.

Moreover, as illustrated in Fig. 1, the edges of the texture and the light pattern appear together on the object's surface. These methods fail to distinguish between these two types of edge. One of the reasons is that, these methods only use information from the source image, where the stripes are expressed as the artificial texture of the object.

In our approach, the structured light based depth imaging provides a means of using a patterning source as part of the blur estimation. By normalising the stripe image with these two reference black and white patterns, we can eliminate the effect of the surface properties such as texture, colour content, etc., hence keeping the artificial texture to estimate the blur.

The major contributions of the paper are:

- A method to estimate the blur of light patterns, and
- Demonstration of its application using the structured light 3D camera for the automatic multi-stage focus

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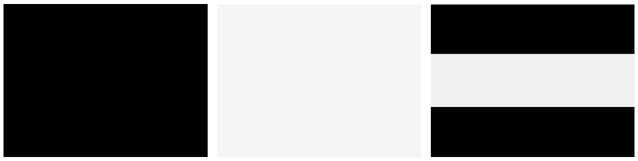


(a) (b) (c)

Fig. 2. 1024x768 size light patterns. Two references: black pattern (a) and white pattern (b). The 1-stripe pattern (c).

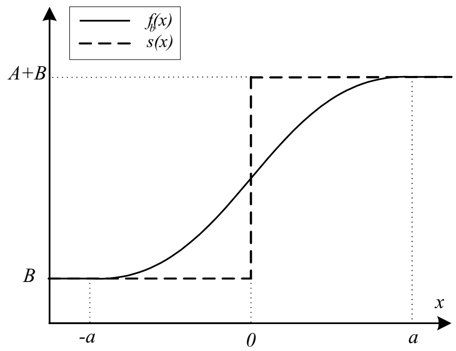


Fig. 3. The blurred edge $f_b(x)$ and the ideal step edge $s(x)$.

control of a beam projector.

The remainder of the paper is organised as follows: In Section II, we describe our blur estimation method. Experimental results are provided in Section III. In Section IV we show the application of blur estimation in automatic projector focus control using a structured light 3D camera and, finally, Section V concludes the paper.

II. The Proposed Blur Estimation Method

We suppose the light pattern is defined by a periodic arrangement with a well defined orientation. Subsequently, we simply analyse the edge along one axis of orientation. When the projector illuminates a black pattern (Fig. 2(a)), the captured image is regarded as the 0-State. The State-0 has an unknown offset B. We assume that a noise $n(x)$ is added to this reference image, which is modelled as a stationary, additive, and zero-mean white noise. The State-0 can be modelled as:

$$f_0(x) = B + n(x) \tag{1}$$

When the projector illuminates a white pattern (Fig. 2(b)), the captured image is regarded as the State-1. The function values are assumed to be equal to the summation of the value of f_0 and unknown amplitude A, which is the amount of reflection property of the object's surface. The State-1 can be expressed as:

$$f_1(x) = f_0(x) + A = A + B + n(x) \tag{2}$$

When the projector illuminates a stripe pattern (Fig. 2(c)). If the object is placed inside of the projector's DOF, the edge of the pattern on the object will be very sharp, we assume that amount of reflection $f_{rb}(x)$ is a step edge. Otherwise, the edge of the pattern on the object will be blurred; thus, $f_{rb}(x)$ is not a step function but gradually increases at the transition area. And the blurred edge $f_b(x)$ is modelled as summation of $f_{rb}(x)$ and State-0, as shown in Fig. 3:

$$f_b(x) = f_0(x) + f_{rb}(x) = f_{rb}(x) + B + n(x) \tag{3}$$

where

$$0 \leq f_{rb}(x) \leq A$$

To eliminate the dependence of the amount of reflection on object's surface properties, we normalise $f_b(x)$ by using $f_0(x)$ and $f_1(x)$, followed by the common noise elimination:

$$\overline{f_b}(x) = \frac{f_b(x) - f_0(x)}{f_1(x) - f_0(x)} = \frac{f_{rb}(x)}{A} \tag{4}$$

where $f_{rb}(x)$ represents blurred edge. We assume the focal blur kernel is Gaussian, so that we can obtain the edge by convoluting a step edge with a blur kernel.

The step edge $s(x)$ is modelled as a step function as illustrated in Fig. 4,

$$s(x) = \begin{cases} A + B & (x \geq 0) \\ B & (x < 0) \end{cases} \tag{5}$$

The Gaussian blur kernel is modelled as a normalised Gaussian function:

$$g(x, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{x^2}{2\sigma^2}\right)} \tag{6}$$

where σ is the unknown blur radius to be estimated.

It follows that the blurred edge $f_{rb}(x)$ is the result of the convolution between the step edge $(s(x) - B)$ and the focal blur kernel $g(x, \sigma)$:

$$f_{rb}(x) = (s(x) - B) \otimes g(x, \sigma) = s(x) \otimes g(x, \sigma) - B \otimes g(x, \sigma) \tag{7}$$

where $\otimes$ denotes the convolution operator. Note that $g(x, \sigma)$ is a normalised function, so that

$$B \otimes g(x, \sigma) = B$$

Thus Equation (7) collapses to a simple form,

$$f_{rb}(x) = s(x) \otimes g(x, \sigma) - B \tag{8}$$

We take the first derivative of the normalised blur edge $\overline{f_b}(x)$

$$\frac{d(\overline{f_b}(x))}{dx} = \frac{1}{A} \frac{d(f_{rb}(x))}{dx} = \frac{1}{A} \left(\frac{d(s(x))}{dx} \right) \otimes g(x, \sigma) \tag{9}$$

The first derivative of the step function is a delta function, as shown in Fig. 4. From (5) we have

$$\frac{d(s(x))}{dx} = A\delta(x) \tag{10}$$

Combining (9) and (10), we have

$$\frac{d(\overline{f_b}(x))}{dx} = \frac{1}{A} A\delta(x) \otimes g(x, \sigma) = \delta(x) \otimes g(x, \sigma)$$

But the convolution of a function with a delta function is the function itself, so that

$$\overline{f_b}'(x) = \frac{d(\overline{f_b}(x))}{dx} = g(x, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{x^2}{2\sigma^2}\right)} \tag{11}$$

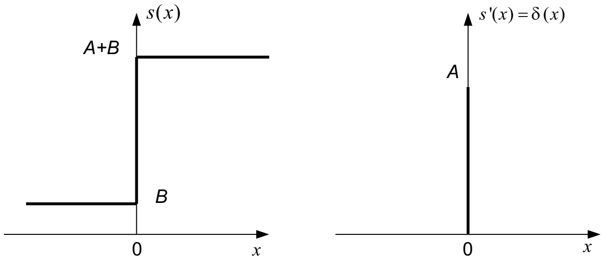


Fig. 4. An ideal step edge (left) and its first derivative (right).

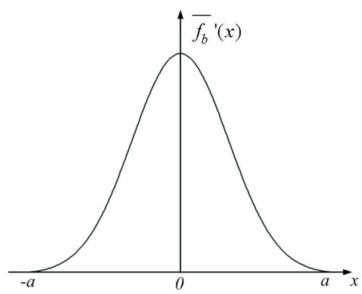


Fig. 5. The first derivative of the blurred edge.

Equation (11) shows that the first derivative of a blurred edge is a normalised Gaussian function. And as shown in Fig. 5, the maximum of a Gaussian function at position $x = 0$. However, the interpretation above uses blurred rising-edge $f_b(x)$ as shown in Fig. 3. Since the σ must be positive, but the first derivative of falling-edge is negative. Thus we get the general blur estimation equation as flows:

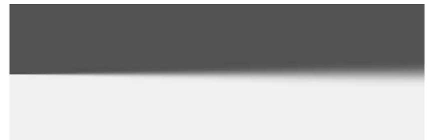
$$\sigma = \frac{1}{\left|\overline{f_b}'(0)\right| \sqrt{2\pi}} \tag{12}$$

From (12), we see that estimated blur radius is not affected by the offset B and amplitude A of the step edge, which represents the property and reflectivity of the object's surface.

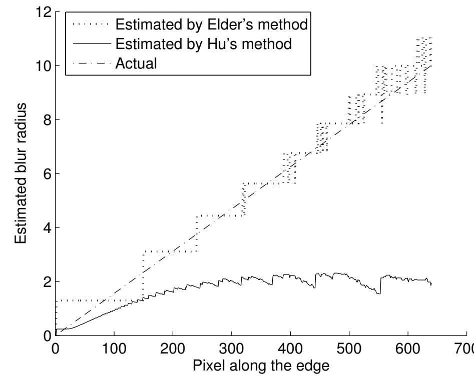
III. Experimental Results

In this section, we show the results of the proposed method on both synthetic and real-test images. We also compare these results with the results of the methods developed by Elder and Hu.

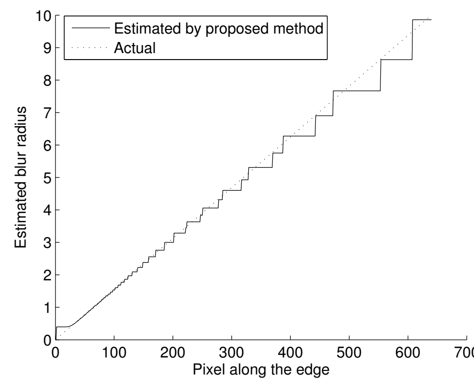
For the synthetic image, we blur the step edge using a Gaussian blur kernel with linear blur radius increases along the edge from 0 to 10, as shown in Fig. 6(a). We experimentally choose the optimal value of σ_2 for Elder's method, and σ_a, σ_b for Hu's method. The estimated blur radii using Elder's and Hu's method are described in Fig. 6(b), and the results of proposed method are shown in Fig. 6(c). As we can see, Elder's method is not sensitive to the change of the blur; and method proposed by Hu gives an erroneous estimation. Whereas the proposed method gives better result compare to those of two methods, especially when the blur is relatively small, as shown in Fig. 6(c). When the blur radius becomes large, it does not affect much on the edge's center but mainly on the slope, thus the height of first derivative's



(a)



(b)



(c)

Fig. 6. Blur estimation with synthetic image. (a) a synthetic image is blurred with increasing blur radius from 0 to 10, from left to right. The estimated blur radius along the edge using Elder's and Hu's method (b), and proposed method (c).

peak does not change much, that why we get the staircase as shown in Fig. 6(c).

With the real-test image, we use different colour papers placed on the same plane in front of the projector. The captured image using a stripe-pattern is shown in Fig. 7(a); two reference images for the proposed method are also captured when projector illuminates black and white patterns. We use Elder's, Hu's and proposed method estimate the blur radius of the stripe's edges along the red line in Fig. 7(a). Fig. 7(b) shows the raw data along the red line, these data are normalised by applying Equation (4), this procedure removes the distortions on the edge caused by the change of the colour and also makes all stripes have approximately same height as shown in Fig. 7(c). Ideally, the estimated blur radius of edges along the red line must be equal due to the same condition. The proposed method has good results that are approximately equal, as illustrated in Fig. 7(d). Whereas the

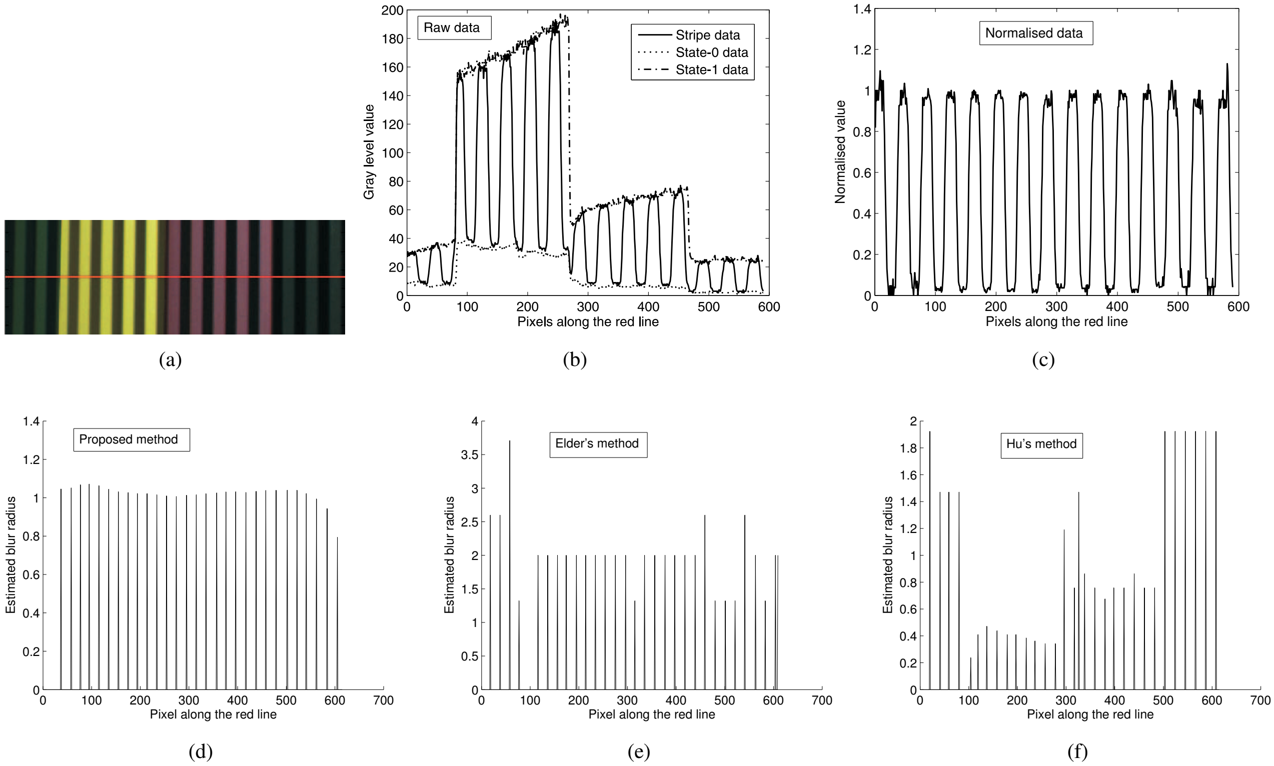


Fig. 7. Blur estimation with real-test image. (a) As part of captured image, the projector projects a stripe-pattern on a board which has different colour papers; the red line indicates the row for estimation with results shown in figures (d)-(f). (b) The raw data along red line and (c) is the normalised data using Equation (4). (d) The result of proposed method. (e) The result of Elder's method. (f) The result of Hu's method.

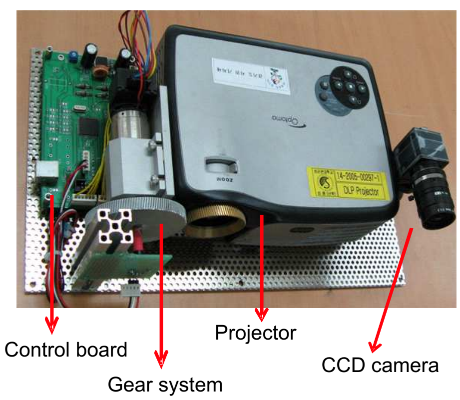


Fig. 8. Setup of the automatic projector focus control system.

results of Elder's and Hu's methods vary depending on the colour of the paper, as shown in Fig. 7(e) and (f).

IV. Application

In this section we show the application of the proposed light pattern blur estimation method in automatic projector focus control in a structured light 3D camera. The hardware setup is shown in Fig. 8. The system consists of: a Flea CCD camera with 1024x768 resolution, Optima EP 729 model projector. A DC motor with the 90-teeth-gear that is linked to the projector's lens in order to control the lens algorithm focus, and a control circuit board that is of responsible for motor control while communicating with the host computer. The structured light 3D point cloud reconstruction has been implemented in conjunction with careful calibration.

During the implementation of the proposed blur estimation method in the auto focus control, we employ the stripes pattern which are defined by a periodic arrangement with a well defined orientation. Consequently, we search and compute the blur of edges along either the columns if the stripes have horizontal direction, or the rows if the stripes have vertical direction. After normalising the image with stripes by the reference images, we differentiate and search for peaks. The centers of the edges can be deduced from the peaks by using the window based search method. Finally, the blur radius is computed using Equation (12). We experimentally choose for blur radius that decides an edge is sharp enough so that the object contains the edge is in focus or not, in our experiment the threshold is chosen with value 0.9.

We set up two objects, one is near ($1m$ from projector) and one is far ($3m$ from projector), while the projector illuminates a horizontal stripe pattern. The lens of the projector is first initialized at the maximum position. The algorithm first controls the lens to focus the light pattern on the box, as shown in Fig. 9(a), the in focus stripes are drawn with red circles. After reconstructing 3D point cloud of the in focus object, the projector's lens is rotated to focus on other objects. The background curtain is put right behind

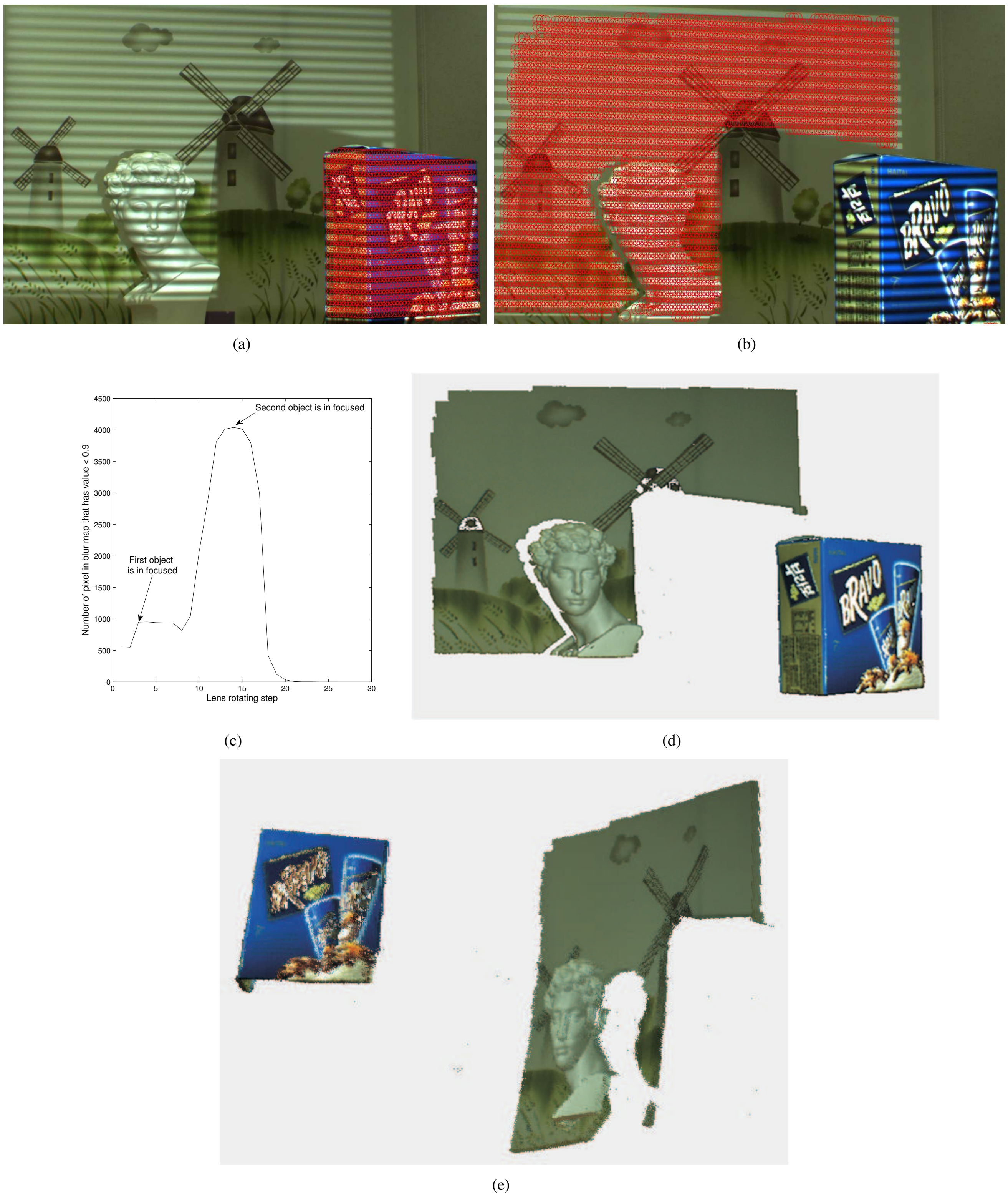
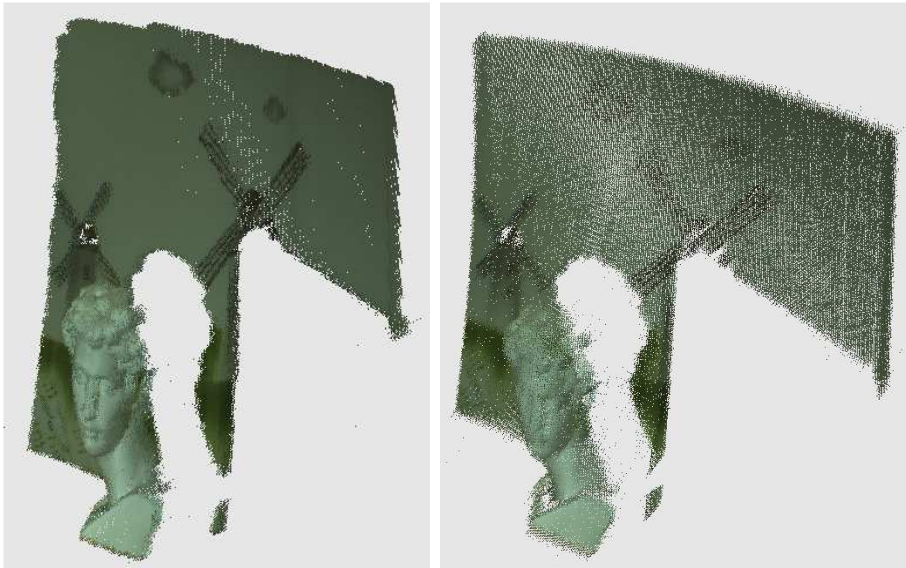


Fig. 9. The box is in focus (a) and the statue and background are in focus (b). The pixels of in-focus stripe's edges are marked with red circles. Graph of pixels of in-focus stripes' edge while rotating projector's lens (c). 3D point cloud of the scene with multi-stage focusing in front view (d) and in side view (e).



(a) (b)

Fig. 10. 3D point cloud in the case of multi-stage focusing (a), and just focus on the box (b) in side-view.

the statue, so that both background and statue are in focus at the same time, as illustrated in Fig. 9(b), the in focus stripes are drawn with red circles. After reconstructing 3D point cloud of the in focus objects, the algorithm continues to rotate the lens to search for in focus object, but there is no more object then the lens is rotated to the minimum position, the graph of the number of in focus pixels in blur map while the lens of the projector is rotating is described in Fig. 9(c). Finally the 3D point clouds of in focus objects are combined to get the complete 3D point cloud of the scene, as shown in Fig. 9(d)-(e). Fig. 10 demonstrates the better result of the multi-stage auto-focusing (Fig. 10(a)) in comparison with the case of fixed projector focus on the box (Fig. 10(b)). In Fig. 10(b), the 3D point cloud has much variation, because when the object is out of focus, the error in finding correspondences between projector and camera (in 3D reconstruction process) will increase. This result demonstrates the significant improvement in the accuracy when apply the light pattern blur estimation based auto-focus control compare with fixed-projector focus in the same structured light 3D camera system.

V. Conclusions

In this paper, we have presented a light pattern blur estimation methods. The experimental results have shown that the accurate and robust blur estimation of a light pattern is shown feasible for a wide variation of surface properties. We have also introduced the application of proposed blur estimation method to automatic projector focus control for robotic applications of structured light 3D camera. The accuracy of 3D point cloud of scene with large depth variation is significantly improved.

References

[1] F. Blais, ”Review of 20 Years of Range Sensor Development”, *Journal of Electronic Imaging*, vol. 13, no. 1, 2004, pp. 231-240.

[2] D. Kim, M. Ryu, and S. Lee, ”Antipodal Gray Codes for Structured Light”, *Proc. of IEEE Int. Conf. on Robotics and Automation*, California, 2008, pp. 3016-3021.

[3] J. Salvi , J. Pags and J. Batlle, ”Pattern codification strategies in structured light systems”, *Pattern Recognition*, vol. 37, no. 4, 2004, pp. 827-849.

[4] M.C. Chiang, T.E. Boult, ”Local Blur Estimation and Super- Resolution”, *Proc. of Conf. on Computer Vision and Pattern Recognition*, 1997, pp. 821-826.

[5] J.H. Elder, S.W. Zucker, ”Local Scale Control for Edge Detection and Blur Estimation,” *IEEE Trans. Pattern Analysis and Machine Intelligence 20*, 1998, pp. 699-716.

[6] H. Hu, G.d. Haan, ”Low Cost Robust Blur Estimator,” *Proc. of IEEE Int. Conf. on Image Processing, Atlanta*, 2006, pp. 617-620.

[7] J.R. Price, T.F. Gee, K.W. Tobin, ”Blur Estimation in Limited-control Environments”, *IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, Salt Lake, 2001, pp. 1669-1672.

[8] F. Rooms, M. Ronsse, A. Pizurica, W. Philips, ”PSF estimation with applications in autofocus and image restoration,” *Proc. 3rd IEEE Benelux Signal Processing Symposium*, Leuven, 2002, pp. 13-16.