An Adaptive Grid-Point Detection Method in a Pseudo-Random Structured Light Pattern

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***Abstract*—In this paper, an adaptive grid-point detection method is developed in a pseudo-random color pattern. In the proposed method, weighted cross mask convolution and non-maximal suppression are carried out to the pattern to obtain several grid-point candidates. In order to accurately measure the point symmetry of the candidates, Harris corner detector is used to adaptively select the suitable window size. Finally, the grid-points are recognized by comparing the symmetry characteristic with a given threshold. Some experiments have been conducted to demonstrate the effectiveness of the proposed method.**

Keywords-feature detection; pseudo-random color pattern; Harris corner detector; structured light

I. INTRODUCTION

Structured light based system, which makes use of a single pseudo-randomly coded pattern in the projection, is an efficient and affordable mean for dynamic 3D recovery [1, 2]. The feature points extracted from the pseudo-random color pattern play a key role for the reconstruction behavior. Furthermore, promising results have been achieved by applying the grid-points between the pattern elements instead of the centroids of the elements as the features [3, 4].

Many schemes can be adopted to detect the grid-points. The grid-points between the neighboring rhombic elements actually are X shape corners. Unfortunately, some traditional corner detectors, such as LoG detector [5], Harris corner detector [6], SUSAN detector [7] etc., can not accurately detect the corners in this situation. The reasons lie in that the rhombic elements are distorted due to the change of object surface. Furthermore, the illumination and the color of the object surface also affect the detection results. In our previous work, a two-fold symmetry based grid-point detector has been proposed for the feature detection of a pseudorandom color pattern in which the local geometrical property but not image intensity is considered [8]. And an adaptive grid-point detector is developed to improve the former detector by exploiting local entropy map [9].

In this work, we propose an adaptive grid-point detection method in a pseudo-random color pattern. The image is firstly convoluted with a weighted cross mask, and then a non-maximal suppression process is carried out. Several preliminary grid points are obtained. After that, we measure the point symmetry of these points. As aforementioned, Harris corner detector is not able to accurately detect the positions of grid-points, but it can be applied to adaptively estimate the window size in the measure of point symmetry. The large number of corners, obtained by Harris corner detector, indicates that this region is intensive such that the size of the circle window should be small. Otherwise, the size of the circle window should be large. Finally, the grid-points are recognized by comparing the symmetry characteristic with a given threshold.

The rest of the paper is organized as follows: Section II briefly reviews the Harris corner detector. Section III presents the proposed method in detail. Experimental results are shown in section IV, and the conclusions are offered in section V.

II. RELATED WORKS

In this section, the pseudo-random color pattern and the widely used Harris corner detector are briefly introduced.

A. Pseudo-Random Color Pattern

In this paper, we consider the grid-point detection problem in a pseudo-random color pattern. The pseudo-random color pattern is generated from a pseudo-random array of size 65×63 as shown in Fig. 1. By the property of the pattern, every window of size 2×3 in the pattern is unique upon the colored elements the window is composed of. Since the pseudo-random array is constructed over GF(4) (Galois Field with 4 elements), we use 4 different colors (Red, Green, Blue, and Black) for the foreground in the pattern, and the white color for the background. While the traditional methods use the centroids of pattern elements as the feature points, in our system we use the grid-points between the neighboring rhombic elements as the feature points.

B. Harris Corner Detector

Let the grayscale 2-dimensional image given by I . Consider taking an image patch over the area (x, y) and shifting it by (u, v) . The sum of square differences between these two patches, denoted as S , is calculated as

$$S=\sum_{u}\sum_{v}(I(x, y)-I(x+u, y+v))^2 . \qquad (1)$$

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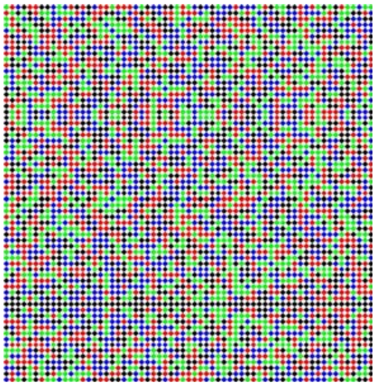
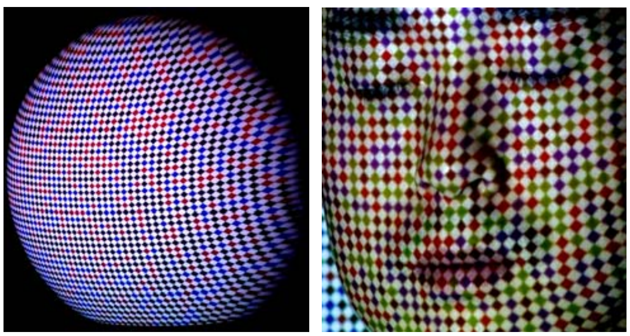


Figure 1. The pseudo-random pattern consists of 65×63 rhombic elements colored in Red, Green, Blue and Black, and the grid-point between pattern elements are defined as the pattern features.



(a) (b)

Figure 2. Example images obtained from the pseudo-random structured light system.

$I(x+u, y+v)$ can be approximated using a Taylor expansion truncated to the first order terms, then (1) can be written in matrix form:

$$S = [u, v]A\begin{bmatrix} u \\ v \end{bmatrix}, \tag{2}$$

where $A = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$, and I_x, I_y represent the first order partial derivatives of the image I along horizontal and vertical directions.

Denote by ∇I the gradient image of I. The matrix A is usually calculated by averaging the tensor product $\nabla I \cdot \nabla I^T$ over the patch with a Gaussian function. In order to avoid the expensive computation of the eigenvalues, Harris suggested that the following response function

$$R_c = \det(A) - k \cdot trace^2(A), \tag{3}$$

where $\det(A)$ and $trace(A)$ are the determinant and trace of A respectively, and k is a tunable parameter whose values are in the range $0.04-0.15$. For more details of Harris corner detector, refer to [6].

III. Method

In this section, we will describe the proposed method in details. The patterns obtained form the pseudo-random structured system are displayed with color images, as shown in Fig. 2.

The proposed adaptive grid point detector can be summarized to the following steps:

- *Step 1:* The image is firstly convoluted with a weighted cross mask. The grid points and their neighboring points may obtain higher values.
- *Step 2:* A non-maximal suppression process is carried out to get the preliminary grid points.
- *Step 3:* Extract the corners making use of Harris corner detector, and then decide the window size based on the distribution of corners. Calculate the symmetry characteristic around these grid-point candidates with different window size.

A. Weighted Cross Mask Convolution

From Fig. 2, it can be observed that the grid–point in rhombic pattern is characterized by the presence of neighboring regions of drastically different intensities in the vertical and horizontal directions. Based on this property, we have proposed a mask in the shape of a cross to hypothesize the positions of grid-points in the image in our previous works. By convoluting the image with the cross mask, the difference of cross section intensity could reach to a relative high score at the grid-point position.

Note that it is difficult to select an optimal size for the cross mask because the rhombic elements are distorted due to the change of object surface. To settle this problem, we propose a weighted cross mask in which the weight is inverse-proportional to the distance between the position and the center. As a result, the absolute difference d, the response value of the mask at any image position (x, y), can be expressed as

$$d = \left| \sum_{i=-l}^{l} I(x+i, y)\cdot e^{-k\cdot i} - \sum_{j=-l}^{l} I(x, y+j)\cdot e^{-k\cdot j} \right|, \tag{4}$$

where l indicates the size of the cross mask, and k is a tunable parameter. The positions with high response values d are kept as candidates of grid-points in the image.

B. Non-Maximal Suppression

As aforementioned, positions with high response values are regarded as the candidates of the grid-points. Dislike our previous work, we carry out a non-maximal suppression process to select the candidates of grid-points. In [9], a pre-specified threshold is set to remove some candidates. However, some grid-points with low contrast (such as the points in the lip of the real human face pattern in Fig. 2(b)) are also thrown away. To avoid above problem, we apply the non-maximal suppression method instead of the fixed threshold. The candidates are kept on condition that their responses are largest in a given region.

C. *Adaptive Symmetry Measure*

There exists a strong two-fold symmetry by the circular neighborhood of a grid-point, and we exploited the coefficient of correlation between the circle window and the 180° rotation of it to measure the strength of the two-fold symmetry in our previous work. The size of the circle window plays a key role in the symmetry measure. Take Fig. 2(a) for an example, the left intensive area should apply circle window with small size, while the right side of the ball should use the circle window with large size.

A method is proposed to adaptively select the window size. Harris corner detector is firstly performed to the image, and some "corners" can be extracted. Although Harris corner detector can not correctly find the grid-points, the results reflect the distribution of the grid-points. Consider the number of "corners" in a given region. The large number indicates that this region is intensive such that the size of the circle window should be small. On the other hand, the size of the circle window should be large if the "corner" number is small.

After calculating the size of the circle window, the point symmetry is measured. Define W as the pixels in a circular window centered at a grid-point candidate position p with a suitable size, and M as the pixels in the window obtained by rotating W by 180° around p . The Pearson's Product-Moment Correlation Coefficient is adopted to measure the symmetry, which is defined as:

$$r_p = \frac{\sum_{i=1}^{N_p}(W_i - \overline{W}_i)(M_i - \overline{M}_i)}{\sqrt{\sum_{i=1}^{N_p}(W_i - \overline{W}_i)^2 \sum_{i=1}^{N_p}(M_i - \overline{M}_i)^2}}, \quad (5)$$

where N_p is the size of the window, $\overline{W}$ and $\overline{M}$ indicate the average of all elements in the window and its rotated version. A candidate grid-point is recognized as a true grid-point if its symmetry characteristic r_p is larger than a given threshold.

IV. Experimental Results

Some experiments are carried out to evaluate the performance of the proposed method in this section. The structured light system in our experiments consisted of a DLP projector of resolution 1024×768 and a camera of resolution 1500×1000 pixels, both being off-the-shelf equipments. As shown in Fig. 2, the experiments are conducted on a spherical object and a real human face respectively.

To make a comparison, two commonly used methods, Harris and SUSAN detectors are also conducted. The experimental results of the spherical object using all the methods are illustrated in Fig. 3. We can find that Harris and SUSAN detectors usually detect the wrong points beside the true corner. The proposed method outperforms over the other two methods. The grid-point detection results of all the methods for the real human face are shown in Fig. 4 respectively. Harris detector is able to correctly detect some corners in this situation, but the result is not satisfying. The proposed method obtains the best performance.

V. Conclusions

An adaptive grid-point detection method has been presented for a pseudo-random color pattern in this paper. Some grid-point candidates are firstly extracted by making use of weighted cross mask convolution and non-maximal suppression. Then the point symmetry is measured in a window with adaptive size. The grid-point is finally recognized by the symmetry characteristic. Some experiments have been conducted to demonstrate the effectiveness of the proposed method. Future work will aim to improve the accuracy of the proposed method.

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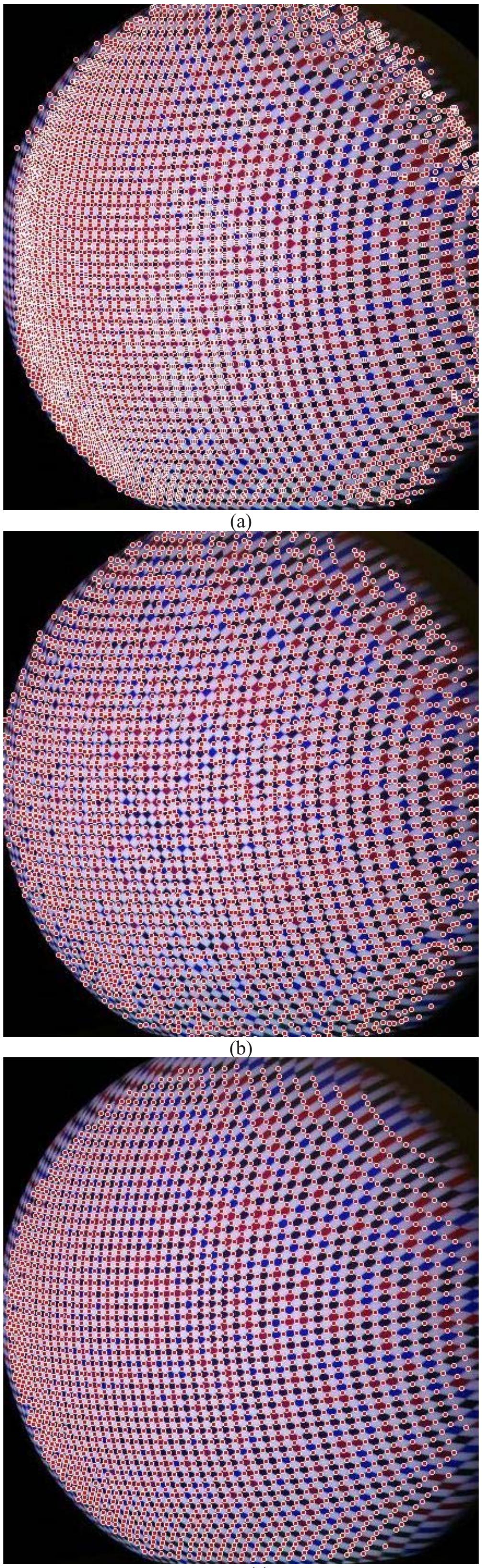

Figure 3. Grid-point detection results on a spherical object via: (a) Harris detector; (b) SUSAN detector; (c) Proposed method

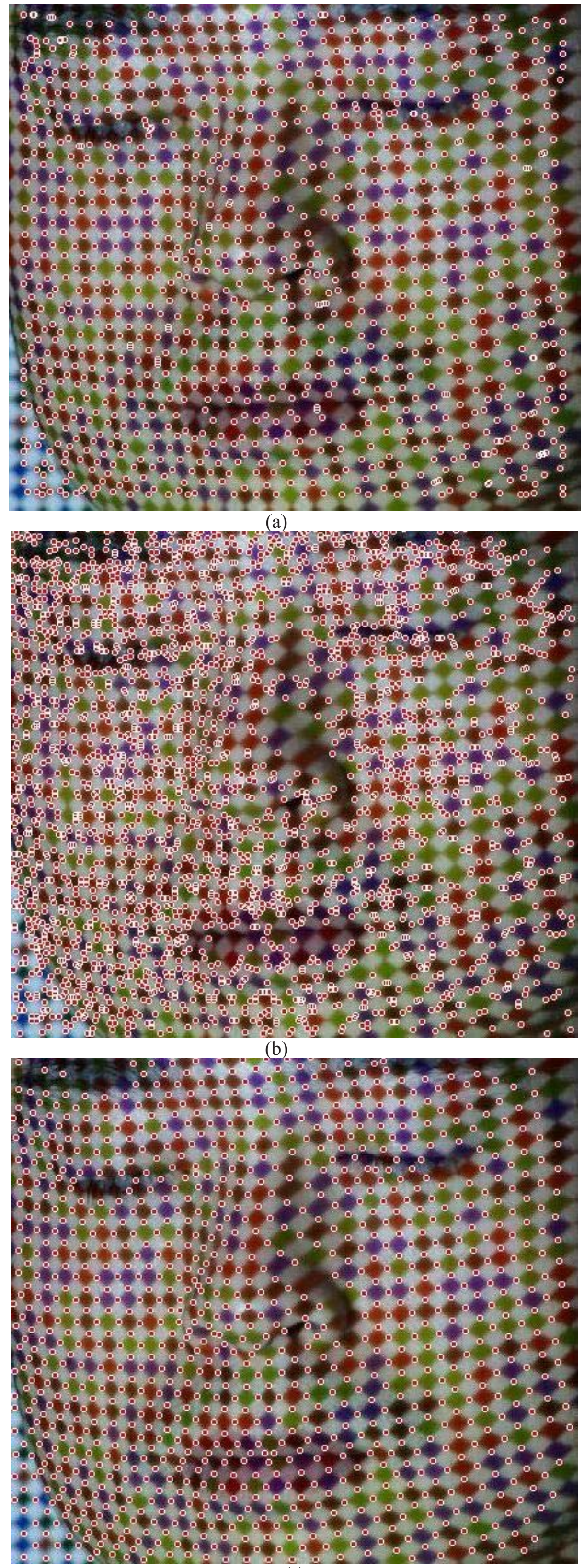

Figure 4. Grid-point detection results on a real human face via: (a) Harris detector; (b) SUSAN detector; (c) Proposed method