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A Corner Detection Method in a Pseudo-Random Structured Light Pattern

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***Abstract*— This paper describes a corner detection method in a pseudo-random structured light pattern. In the algorithm, the image is firstly convoluted with a weighted Gaussian mask (WGM) in which the symmetry property between two neighboring rhombic elements is considered. As a result, the proposed method is more suitable to detect the X shape corner in the structured light pattern. Then a non-maximal suppression process is carried out to find the candidates for the corner. Record the times of each position being the candidate in different size of WGMs. Finally, the fuzzy c-means (FCM) algorithm is conducted to determine the threshold for being the corner. Some experiments have been conducted to demonstrate the effectiveness of the proposed method.**

I. Introduction

CORNER detection is an important task in various computer vision, image processing, and pattern recognition systems since corners are significant features of an image. Applications that rely on corners include motion tracking, object recognition, 3D object modeling, stereo matching, etc.

Considerable attentions have been paid on corner detection, and a large number of successful detectors have been proposed. Some widely applied approaches in the literature are the LoG [1], Harris [2], and SUSAN [3] detectors. Well-known as one of the earliest successful method, Harris corner detector calculated the first-order derivatives of the image along horizontal and vertical directions, with which a 2×2 structure tensor was formed. Then the corner detection was accomplished by analyzing the eigenvalues of the structure tensor at each pixel. SUSAN (Smallest Univalue Segment Assimilating Nucleus) detector is another popular used scheme. Recently, some novel methods [4], [5] have been proposed, and satisfying results are achieved.

In this paper, we consider the corner detection problem in a pseudo-random structure light pattern [6], [7]. The structured light 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 [8], [9].

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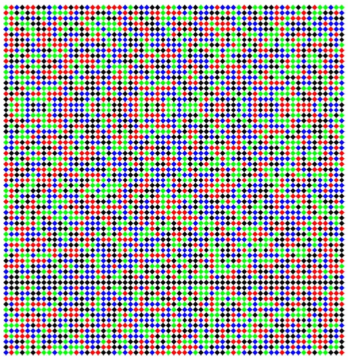
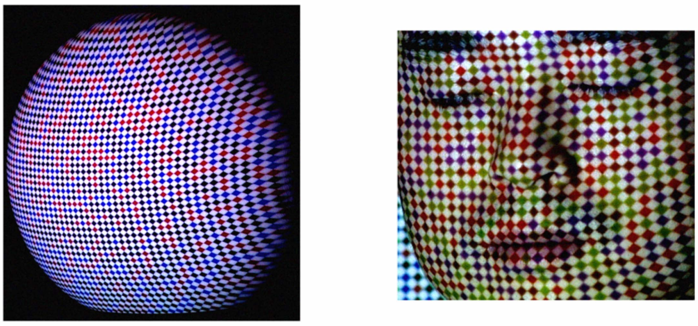


Fig. 1. Pseudo-random pattern consists of 65×63 rhombic elements colored in Red, Green, Blue and Black, and grid-point between pattern elements are defined as the pattern features and then encoded.

Observing Fig. 1, we may find that the grid-points between the neighboring rhombic elements actually are X shape corners. However, some traditional methods 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.

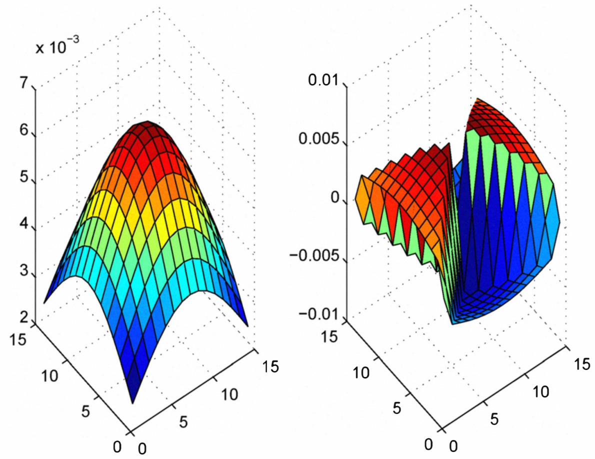
In this work, we propose a corner detection method for the pseudo-random structured light pattern. The image is firstly convoluted with a weighted Gaussian mask (WGM). Dislike the ordinary Gaussian mask, the developed WGM considers the symmetry property between two neighboring rhombic elements. Then a non-maximal suppression process is carried out. Record the positions of the left points. These points are viewed as the candidates for the real corners. Change the size of weighted Gaussian mask and repeat the former steps. The times that each position being the candidate in fact is the possibility for being a corner point. Finally, fuzzy c-means (FCM) is conducted to determine the threshold for being the corner. Experiments on different objects are conducted to demonstrate the effectiveness of the proposed method.

The rest of this paper is organized as follows: The proposed method is given in Section II, and some experiments are carried out to evaluate the proposed method in Section III. Finally, Section IV concludes the paper.



(a) (b)

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



(a) (b)

Fig. 3. (a) Traditional Gaussian Mask; (b) Weighted Gaussian Mask.

II. Method

In this section, we will describe the proposed method in details. The pattern obtained from pseudo-random structured light system are displayed with color image, as shown in Fig. 2. The color image is firstly converted to gray-scale image for corner detection.

A. Weighted Gaussian Convolution

From Fig. 2, it can be observed that any corner-point on the pattern generation plane of the projector then has a local circular neighborhood presenting perfect two-fold symmetry. We develop a mask to measure this property. The mask is an antisymmetric matrix whose main diagonal and secondary diagonal diagonal elements are set to be 0. And the two diagonal lines divide the matrix into four parts. In the developed matrix, the elements in the two horizontal parts are set to be 1, while the elements in the two vertical parts are set to be -1. For example, we show a mask with size 7×7 as following:

$$M(x,y) = \begin{pmatrix} 0 & -1 & -1 & -1 & -1 & -1 & 0 \\ 1 & 0 & -1 & -1 & -1 & 0 & 1 \\ 1 & 1 & 0 & -1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & -1 & 0 & 1 & 1 \\ 1 & 0 & -1 & -1 & -1 & 0 & 1 \\ 0 & -1 & -1 & -1 & -1 & -1 & 0 \end{pmatrix}.$$

Note that some corner points, the rhombic elements are distorted due to the change of object surface. To reduce the affect of distortion, we multiply the elements in the above mask with different coefficients according the positions. The elements, which are closed to the center, are with larger coefficients. In this paper, we make use of the following 2D Gaussian function to generate the coefficients:

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}. \tag{1}$$

The final mask, referred to as weighted Gaussian mask (WGM), is given as following:

$$WGM(x,y,\sigma) = M(x,y). * G(x,y,\sigma), \tag{2}$$

where $.*$ denotes the array multiply operation. Fig. 3 illustrates an example of WGM. Fig. 3(a) shows a traditional Gaussian mask with size 17×17, and Fig. 3(b) shows the WGM with the same size.

Then the image $f(x,y)$ is convoluted with WGM,

$$F(x,y,\sigma) = WGM(x,y,\sigma) * f(x,y), \tag{3}$$

where $*$ is the convolution operation in x and y. In the corner position, the absolute value of $F(x,y,\sigma)$ is maximal in a local region.

B. Non-Maximal Suppression

A non-maximal suppression is followed by the weighted Gaussian convolution. Suppose the size of the used WGM is $n_1 \times n_1$. The non-maximal suppression is performed in a $(n_1+2) \times (n_1+2)$ region Ω. Let Max_F and Max_Ω denote the maximal value of $F(x,y,\sigma)$ and the region Ω respectively. Then the non-maximal suppression is conducted as following:

$$F'_{n_1}(x,y,\sigma) = \begin{cases} 1, & \text{if } F(x,y,\sigma) > \frac{3}{4}\mathrm{Max}_\Omega \text{ and } \frac{1}{4}\mathrm{Max}_F; \\ 0, & \text{else.} \end{cases} \tag{4}$$

From Eq.(4), $F(x,y,\sigma)$ is restricted to larger than $\frac{3}{4}\Omega$ such that more points around the corner can be selected to be candidates. On the other hand, $F(x,y,\sigma)$ is also required to bigger than $\frac{1}{4}\mathrm{Max}_F$ with the purpose of eliminating some false corners. The positions of non-zero elements in $F'_{n_1}(x,y,\sigma)$ are candidates of corners.

C. Corner Determination using FCM

In this part, we will reveal how to detect corners making use of FCM. To begin with, the FCM algorithm is briefly reviewed.

1) FCM algorithm: FCM is an unsupervised clustering technique, and has been successfully applied to feature analysis, target recognition, classifier designs, and image segmentation etc. Let $X = (x_1, x_2, \ldots, x_N)$ denotes N samples to be partitioned into c clusters. c is assumed to be known. FCM aims to minimizes the objective function defined as follows [10]:

$$J_{\text{FCM}} = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \|x_j - v_i\|^2, \tag{5}$$

where u_{ij} represents the membership of the sample x_j in the ith cluster, v_i is the ith cluster center, m is a constant, and $\|\cdot\|$ represents the standard Euclidean distance. The parameter m is a weighting exponent on each fuzzy membership, and is usually set to be 2.

The objective function is minimized when the samples, which are closed to the centroid of their clusters, are assigned high membership values, while low membership values are given to pixels with data far away from the clustering centroid. The membership function represents the probability that the sample belongs to a specific cluster.

Taking the first derivatives of the objective function with respect to u_{ij} and v_i and setting the equations to 0 will obtain necessary conditions for Eq.(5) to be minimized. Using a Picard iteration through these two necessary conditions, the membership functions and cluster centers are updated by the following respectively:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{2/(m-1)}}, \tag{6}$$

and

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}}. \tag{7}$$

Beginning with an initial value for each cluster center, the FCM converges to a solution. For more details of FCM, refer to [11].

2) Corner Determination: As aforementioned, $F'_{n_1}(x, y, \sigma) = 1$ indicates that the position (x, y) is a candidate for a corner with a $n_1 \times n_1$ WGM. Similarly, we may obtain $F'_{n_2}(x, y, \sigma), F'_{n_3}(x, y, \sigma), \cdots, F'_{n_k}(x, y, \sigma)$ by setting the size of the WGM to be $n_2 \times n_2, n_3 \times n_3, \cdots, n_k \times n_k$.

Then calculate the following formula

$$I(x, y) = \sum_{i=1}^{k} F'_{n_i}(x, y, \sigma). \tag{8}$$

$I(x, y)$, in fact, is the times that the position (x, y) being the candidate for a corner. The more times, the higher possibility to be a corner. Based on $I(x, y)$, we apply FCM to determine the threshold for being a corner. Finally, we may obtain the accuracy position of the corner.

III. Experimental Results

In this section, experiments are carried out to evaluate the performance of the proposed method. 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.

Two commonly used methods, Harris and SUSAN detectors are also conducted for a comparison. Fig. 4 illustrates the corner detection results of all the methods for the spherical object. We can find that Harris and SUSAN detectors usually detect the points beside the corner. The proposed method outperforms over the other two methods. The corner detection results of all the methods for the real human face is given in Fig. 5. Harris detector correctly find many corners in this situation, and the proposed method obtains the best performance.

IV. Conclusions

In this article, we have presented a corner detection method for the rhombic pseudo-random pattern. To consider the symmetry property between two neighboring rhombic elements, we propose a weighted Gaussian mask (WGM). The corners are detected by weighted Gaussian convolution, non-maximal suppression, and FCM cluster steps. Some experiments have been conducted to demonstrate the effectiveness of the proposed method. Our future work will aim to improve the robustness of the proposed method.

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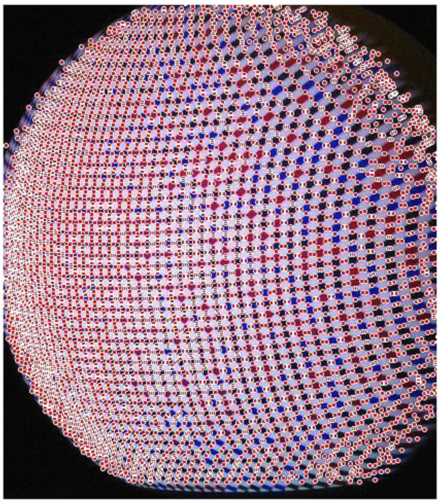
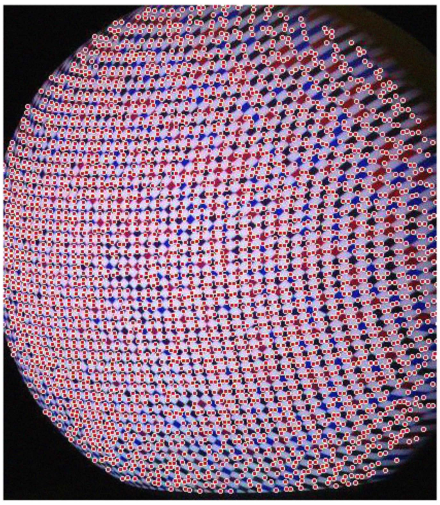


(a)



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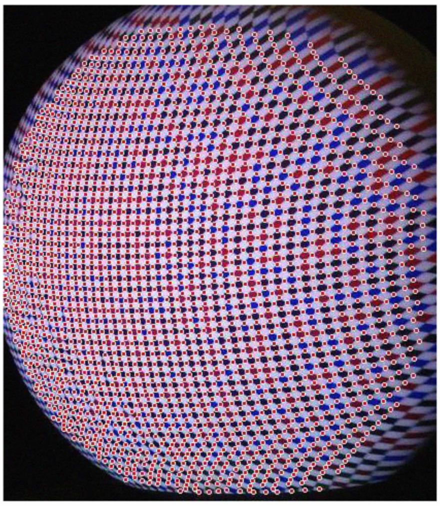
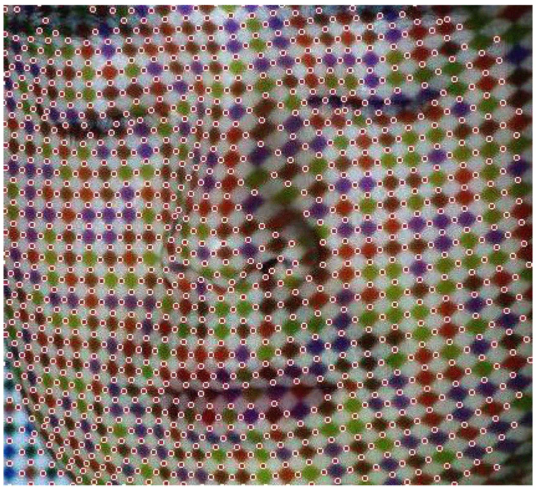


(c)

Fig. 4. Corner detection results on a spherical object of three methods: (a) Harris corner detector; (b) SUSAN corner detector; (c) proposed corner detector.

(a)

(b)



(c)

Fig. 5. Corner detection results on a real human face of three methods: (a) Harris corner detector; (b) SUSAN corner detector; (c) proposed corner detector.