A Twofold Symmetry based Approach for the Feature Detection of Pseudorandom Color Pattern

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***Abstract* –Spatially encoded structured light technique is an important means for the dynamic 3D reconstruction. This paper first present a novel designed pattern, which adopts four color elements and get a 2×2 unique window property. To detect the pattern features, i.e. the grid points, a twofold symmetry based feature detection method is investigated. The value of each pixel is firstly computed in *R, G, B* channels respectively. And the largest one is select to represent the pixel. By selecting the local maximum points as feature candidate, a measurement of twofold rotation symmetry is proposed to localize the grid point precisely. With comparison with some classical detectors and experiment with real human face, the robustness and accuracy of the proposed detector is demonstrated.**

Keywords – pseudo-random color pattern, grid point, feature detection, structured light.

I. Introduction

Structured Light Sensing (SLS) has been an important research area in computer vision domain. According the coding strategies adopted in various SLS systems, it can be generally divided into spatial coding and temporal coding [1]. For the temporal coding method, it usually takes multiple projections. By analyzing the change of image intensity along temporal axis, the surface point can be encoded uniquely. As for the spatial coding method, it takes only one projection. The pattern features can be encoded via its neighboring image intensity or colors. In comparison, temporal coding can achieve high robustness and reconstruction accuracy, and the spatial coding can achieve high reconstruction efficiency since it only needs one image and projection. However, how to design the spatial SLS pattern to improve its coding density and how to decode such coding features robustly is still a challenging work in this research area.

M-array is the most widely used coding principle in spatial SLS [2]. The constructed pattern image has a distinct advantage of unique window. Such a window only appears once through the whole image, and thus can be used to solve the corresponding problem. The pattern elements are usually designed to various color blocks. While the pattern is projected to the target surface, it is usually blurred and fused with the surface texture or colors. The extraction of the projected pattern features is usually named as pattern decoding. Feature extraction or detection has been a classical topic in computer vision. And many feature detectors have been proposed in past literatures, such as Harris corner detector [3], Scale-Invariant Feature Transform (SIFT) detector [4], and Speeded up Robust Features (SURF) detector [5] etc. For Harris detector, a matrix of the second derivative of the local neighborhood is computed. And the two eigenvalues of the matrix are used to determine which pixel is a corner point. In the SIFT algorithm, features are defined as maxima and minima of the result of difference of Gaussians function applied in scale space to a series of smoothed and resampled images. Dominant orientations are assigned to localized feature points. This feature detector has distinct advantage of scale invariant. Based on the similar principle of SIFT, SURF detector is implemented on a more efficient way by the use of integral image. In the SURF detector, values of every image point are computed by the Hessian matrix at different scales. After that, non-maximum suppression is applied in a 3×3×3 neighborhood to detect the interest points. In [6], an ideal corner is assumed with a corner structure which has an annulus mask. In [7], a robust corner detector is proposed based on the principle of Features from Accelerated Segment Test (FAST) algorithm. It improves the localization accuracy and also reduces the computational time. All these feature detectors are proposed for some general purpose in computer vision, such as the corresponding problem. But for the SLS applications, the features are usually specified and with higher robustness and precision requirements.

For most pseudorandom coded SLS pattern, the feature is usually defined as the intersection points of adjacent pattern elements. Such a feature usually appears as X-shape or grid-point. In [8], a checker-board like pattern is designed, and the grid-point is detected via a specially designed binary feature detector. In [9], a color pseudorandom pattern is presented, and a corner symmetry detector is introduced to detector the grid-points. In [10], an adaptive detector is proposed by using the local entropy map. However, it is only applicable to the pattern elements with homogeneous colors. Generally, in SLS, the feature detector is usually designed for specific structured light pattern according to its structure characteristics.

In this work, a novel designed pseudorandom pattern is firstly introduced. It adopts four different colors, but can

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realize a 2×2 window property. In comparison with traditional 2×3 window size, the smaller unique can distinctly relieve the difficult in decoding procedure. To extract the pattern features from the images, each pixel is computed in R, G, B channels and the largest one is select to represent the pixel. After that, we select the local maximal points to be candidate grids. Finally, a measurement of twofold rotation symmetry is proposed to find the true grid points. Experiments on a variety of object are implemented with a comparison to some classical feature detectors to show it high robustness and accuracy.

II. Pseudorandom Pattern Design

In our past work, a pseudorandom pattern has been presented in [11]. In this pattern, it utilizes four different colors, say R, G, B and K. The pattern is constructed over Galois Field with 4 basics or *GF*(4). It can obtain a pattern with size of 65×63, with a unique window size of 2×3. That means, for a grid point, it has 6 adjacent elements to be identified. In this work, we improve this coding strategy by extending the coding domain to *GF*(8). We still take 4 colors in the pattern, but introduce some embedded pattern elements. The number of colors is not changed, but the unique window can be shrunk to 2×2. The primitive polynomial used to generate the pseudo-random array is defined as:

$$h(x) = x^4 + x + \alpha^3 \tag{1}$$

The sequence is computed using the equations:

$$\alpha^3 + \alpha + 1 = 0, \quad \alpha^7 = 1 \tag{2}$$

Every nonzero element of *GF*(8) is a power of α, i.e. α is a primitive element. And every element of *GF*(8) is a binary linear combination of $\{1, \alpha, \alpha^2\}$. With the given primitive polynomial, we can get a pseudo-random sequence, and a pseudo-random array can be produced by a folding process [2]. Compared with the pattern in [11], size of the window can be reduced to 2×2. However, it has to introduce more color elements. With the usage of more colors, the decoding work is even more difficult to deal with textured surface. To avoid more colors be used, a novel pattern element definition is presented in this work. We used four solid colors (R, G, B and K) and four hollow colors as the pattern elements. White color is embedded to the solid color elements to form the embedded elements. With such a design, both color and geometrical features can be fully utilized, and facilitate the final pattern decoding issue. The constructed pattern is as shown in Fig. 1.

The unique window with size of 2×2 is displayed in Fig. 2. And there are two types of codeword. The codeword of any grid point can be either *P1* type or *P2* type. For every grid point, its codeword is unique in all of grid points which have the same type. So in the pattern, we can use the type and the codeword to uniquely distinguish all grid points. We can also see that if we want to get the codeword of a grid point, we only need to identify four elements, and its code value can be expressed as *c*1-*c*2-*c*3-*c*4.

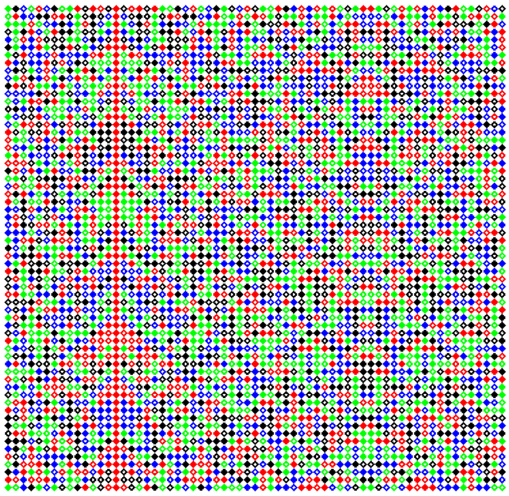


Fig. 1. The constructed pseudorandom pattern over *GF*(8). It utilizes 4 colors and their embedded shape. The pattern size is 65×63 with a unique window size of 2×2.

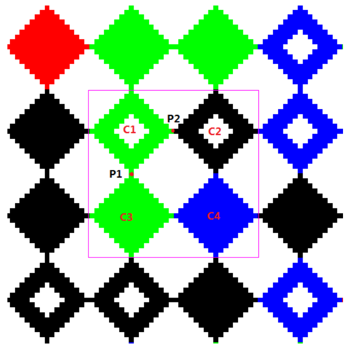


Fig. 2. There are two type of grid point, P1 and P2, and they share the same code value of *c*1-*c*2-*c*3-*c*4.

III. Grid Point Detection via Twofold Symmetry Feature Descriptor

In [10], we have proposed an adaptive grid-point detector with respect to the pattern described in [11]. However, such a feature detector only works well to the solid color elements. But after the embedded color element is added, the local structure of the pattern element is changed, and the performance of feature detector is degraded greatly. The most important factor is that the corners of embedded diamonds are similar to the grids between rhombic elements. So if we use their grid-point detector, we will detect some false grids. In this section, we will show how the feature detector can be improved to well treat the newly designed pattern.

A. Detection of Candidate Grid Point

Firstly, we should detect the candidate grid points from all of the pixels. For each image pixel, we use the cross mask to compute its values in *R, G, B* channels respectively. Each value is the difference of the intensity in the channel along cross section. The operation can be formulated as:

$$d_R = \left| \sum_{\alpha=-L}^{L} p(i+\alpha, j, 1) - \sum_{\beta=-L}^{L} p(i, j+\beta, 1) \right|$$
$$d_G = \left| \sum_{\alpha=-L}^{L} p(i+\alpha, j, 2) - \sum_{\beta=-L}^{L} p(i, j+\beta, 2) \right| \quad (3)$$
$$d_B = \left| \sum_{\alpha=-L}^{L} p(i+\alpha, j, 3) - \sum_{\beta=-L}^{L} p(i, j+\beta, 3) \right|$$

where *p(i, j, 1)* is the *R* value of the pixel *(i, j)*, and the same as *p(i, j, 2)* and *p(i, j, 3)*. And *L* means the length of the cross arm centered at the image pixel *(i, j)*. Now every pixel has three values d_R, d_G, d_B . We use the maximum of them as the representative of the pixel as:

$$d(i, j) = \max(d_R, d_G, d_B) \quad (4)$$

While the image is preprocessed with above operation, we can step to the detection of candidate grid points.

In order to reduce the computation load, we select some interest points from all pixels. We divide the image into some square regions. And the pixels with largest local intensity values are selected as the potential interest points. Now we have to find the maximum of all values in the area centered at every interest point. It is defined as:

$$grid = \max(\max(d(i-l:i+l, j-l:j+l))) \quad (5)$$

where *d* is the value matrix of all pixels and *l* is the half length of the area centered in pixel *(i, j)*. If the value of an interest point is the maximum of the area centered itself, the interest point is a candidate grid point.

In the pattern, we use the red, blue, green and black color as the elements and the white color as the background color. So the grid point has the largest value in at least one channel in the neighborhood of self-centered. In this case, we can use this property to detect the candidate points. While, some embedded corners may also have this property. In the next step, we will introduce a twofold symmetry based feature detector to determine the accurate position of all grid point.

C. Accurate Grid Point Localization via Twofold Symmetry

In the pattern, twofold rotation symmetry always occurs at the positions of true grid points. It can be used to judge which one is a true grid point from the candidate grid points. The Pearson's Product Moment Correlation Coefficient (PMCC) is usually a good choice to measure whether the candidate grid point is twofold rotation symmetry or not. But to the embedded pattern elements, it cannot work very well. To solve this problem, a new approach is introduced. Suppose *A* be a circular mask centered at a candidate grid point, and *B* is created by the rotation of *A* with 180º, so the symmetrical coefficient can be defined as:

$$\rho = \frac{\frac{1}{mn}\sum_{m}\sum_{n}(A_{mn} - B_{mn})^2}{\frac{1}{mn}\sum_{m}\sum_{n}(A_{mn} - \overline{A})^2} \quad (6)$$

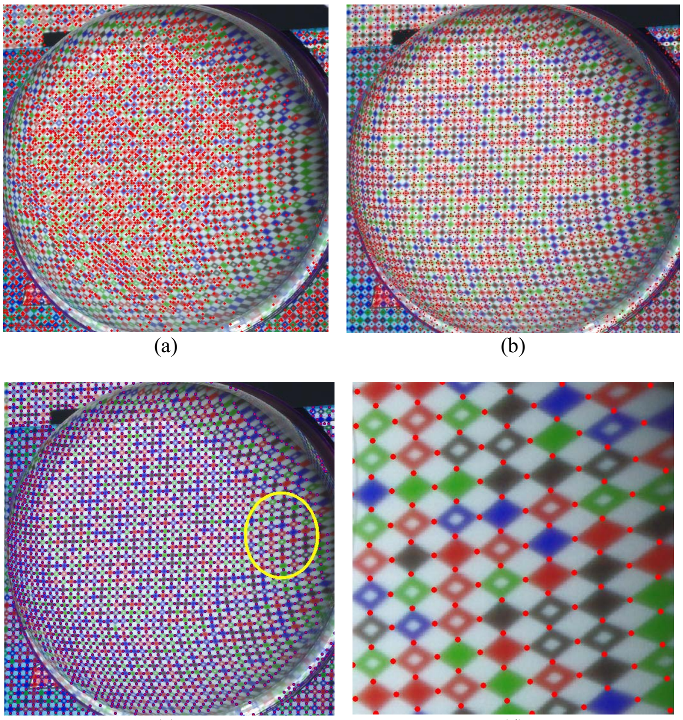
where A_{mn} is the value of the index *(m, n)* element of mask *A*, and B_{mn} is the value of the index *(m, n)* element of mask *B*. $\overline{A}$ is the mean value of the mask. Equation (6) shows the symmetrical coefficient is inversely proportional to symmetry. So when a mask is totally twofold rotation symmetry, its symmetrical coefficient is zero. In the formula, the denominator indicates the variance of the elements in the mask and the numerator means the mean value of the square difference between the corresponding elements in *A* and *B* mask. So, the numerator can directly represent the difference of the two masks and the denominator is used to normalize the difference. With such as difference operation, the intensity difference cause by the embedded white color can be skipped. And thus makes the symmetry property can be preserved overall pattern elements.

IV. EXPERIMENTAL RESULTS

The experimental setup is configured with a DLP projector with resolution of 1920×1080 pixels and a DSLR camera with resolution of 3872×2592 pixels. The algorithm is implemented with Matlab 2010a. The first experiment is conducted on a freeform surface to compare the proposed feature detector with some classical ones like Harris and SURF. Fig. 3(a) shows the result by Harris detector. It detector very dense feature points where gradient change existing. Fig. 3(b) shows the result by SURF detector, it has better result than Harris. But most the detected feature points are located at the central region of pattern elements. In comparison as shown in Fig. 3(c), most of the grid point even at the marginal regions can be well detected with satisfied accuracy.

The second experiment is conducted on a planar surface to compare our grid point detector with the detector in [9]. The results are as shown in Fig. 3. With comparison, we can see that our previous feature detector cannot deal well with the embedded color elements. But the improved feature detector can identify all grid points with accurate localization.

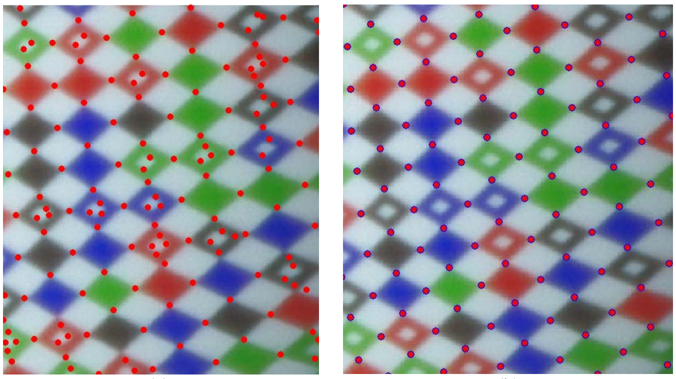
To evaluate its performance on textured surface, a real human face is used for the experiment as shown in Fig. 5. From the result, we can see that the grid point in texture regions such as lips and eyes can still be accurately identified. Moreover, to the regions with big pattern distortion such as the nose, the grid points can still be extracted precisely.



(a) (b)

(c) (d)

Fig. 3. Grid-point detection results. (a) Result by Harris; (b) Result by SURF detector; (c) Result by our method; (d) Enlarged area for close observation.



(a) (b)

Fig. 4. Grid point detection result on a planar surface. (a) Result by our previous feature detector in [9]; (b) Result by our new method, it is immune to the added hollow color elements.

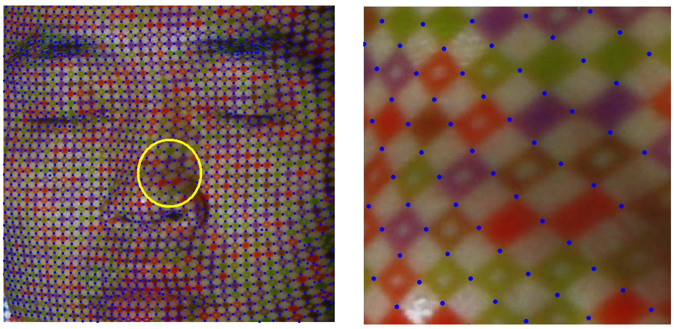


Fig. 5. Grid point detection result on a real human face. The enlarged area is to show its performance in the regions with pattern element distortions.

With above experiments we can see that, the classical feature detector usually utilize the gradient information as feature description, and thus very sensitive to the image noise and some unexpected pattern features. The detection results are also lack of robustness and localization accuracy. In comparison, the proposed method fully utilized the geometrical structure of the special designed pattern. And the operator has distinct advantages of anti-noise, distortion free and localization accuracy.

V. Conclusion and Future Work

In this paper, we present a novel SLS pattern design as well as its feature detection method. The pattern is designed over *GF*(8). To avoid more colors be used, some embedded elements are introduced. To extract the pattern features from the images, each pixel is computed in R, G, B channels and the largest one is select to represent the pixel. After that, we select the local maximal points to be candidate grids. Finally, a measurement of twofold rotation symmetry is proposed to find the true grid points. Experiments on a variety of object are implemented with a comparison to some classical feature detectors to show it high robustness and accuracy. In the future, we will decode the code words of grid points to realize the 3D reconstruction procedure. In addition, how to realize the adaptive mask size selection is also an interesting topic.

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